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Review of the Optimization Machine Learning Inverse of view – Mode Fiber

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A B S T R A C T

The significance of optical fiber research in the digital realm is increasing because of its use in components, sensors, and high-speed data communication. The study of few-mode fiber (FMF) is experiencing a resurgence because of its capability to transmit data at high rates. This dissertation offers novel designs of FMFs with updated material composition and geometry to construct linkages using weakly coupled spatial division multiplexing (SDM) and mode division multiplexing (MDM). This study examines the necessary conditions for 5G networks and explores how they can be managed using spatial multiplexing and mode multiplexing techniques with a few-mode optical fiber. This method showcases the use of machine learning to simulate the profile of a few-mode fiber with a triangular-ring-core structure. It employs weak coupling optimisation to provide accurate predictions of refractive index differences and improved separation of spatial modes. Notably, this is accomplished using a data set that is six times smaller than that used in previous methods.

1. Introduction

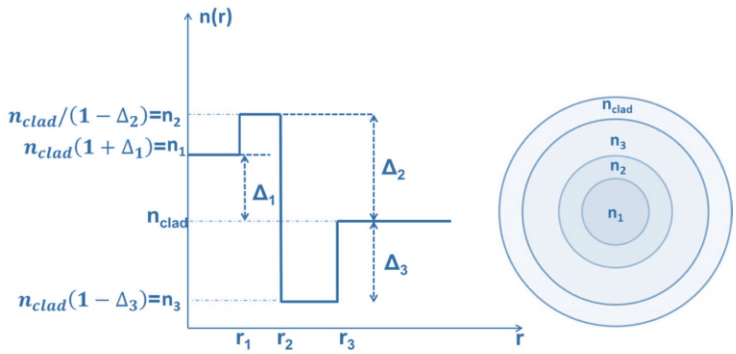
The utilization of several modes in few-mode fiber (FMF) for mode division multiplexing (MDM) is one method that can be utilised to circumvent the capacity bottleneck that is associated with optical communications based on single-mode fiber (SMF) [1,2,3]. MIMO processing, which stands for multiple input, multiple output, is required for tightly coupled systems because of the coupling between modes. This will result in a large rise in both the cost and the amount of power consumed [4,5,6,7]. As a result, a weakly coupled system based on a weekly coupled FMF would be more suitable in high-speed MDM communications because it has a lower complexity in signal processing [8.9]. Specifically, MIMO-less MDM communication can also be accomplished for optical connectors with a short distance [1-15].

The process of implementing a parametric sweep-based FMF design across a complex structure is time-consuming. Obtaining several parameters that fall within the prescribed range through simulation the use of simulation could be a challenging endeavor. The application of machine learning (ML) strategies is an efficient method for resolving difficult tasks. Furthermore, the application of the machine learning approach in inverse modelling is one of the most successful ways to achieve the required answers, particularly in situations where the target is already known [16]. Additionally, the use of the inverse modelling approach in the development of few-mode fibers through the application of machine learning is not only effective but also can be utilised multiple times. For various fiber designs, exact results can be obtained from applying machine learning algorithms and tweaking system parameters. The ML models successfully correlating the data that is being input with the data that is being output, which speeds up the design process. While there has been a deficiency in the amount of effort put forward in this particular domain, there remains the possibility of additional expansion. Therefore, a reverse model is developed to predict the profile parameters of ring-core FMFs (RC-FMFs). The objective of this model is to limit mode coupling (min Δneff < 1 × 10−3) between surrounding LP modes while concurrently increasing the number of guided modes [17-20].

One of the unique approaches to inverse modelling is shown here, which uses a machine learning technique based on regression. The objective of these regression models is to make predictions regarding the profile characteristics of two different RC-FMF structures to improve the transmission of poorly connected MDM. To anticipate a variety of profile parameters, three different regression models are utilised. These models are the ordinary least-square linear regression for multi-outputs, the k-nearest neighbors of multi-output regression, and the ID3 algorithm-based decision trees for multi-output regression. For rapidly modelling RC-FMFs, it has been conclusively established that the ID3-based decision tree is a machine learning model that is both reliable and accurate [21,22].During the first phase of this assignment, you will be responsible for developing a three-ring-core FMF by employing an inverse technique and using the projected profile parameters. Over the past few years, machine learning has emerged as a prominent example of cutting-edge technology innovation. To improve efficiency, produce forecasts, classify data, and create projections, this can be utilised across various disciplines. Using a neural network (NN) to implement machine learning (ML) for inversely building an RC-FMF structure is the approach that has been presented. Weak coupling in step-index few-mode fibers has been demonstrated to be maximized through the implementation of an inverse design, as demonstrated by the authors in [23, 24, and 25]. To guide modes, they used a 4-ring structure. In addition, they modified the profile parameters of a 6-ring structure to achieve 20 modes with weak coupling.

METHOD AND METHODOLOGY

A new RC-FMF has been proposed for weak coupling optimisation and fabrication feasibility. This FMF structure is similar to SIF but has a restricted set of design characteristics. The fiber is created using inverse modelling and machine learning to achieve a specific number of modes with minimal interaction. The proposed design features three rings to simplify the fabrication process and uses silica as the host material. The refractive index profile variation of the ring core is determined by the radial distance, with the first, second, and third rings down-doped to minimize coupling between higher-order modes. The ring radius and refractive index difference are crucial profile characteristics of the proposed FMF [26, 27, 28].The design aims to meet the cost-effective fabrication criterion and improve the efficiency of mode-division multiplexing transmission. The proposed FMF is assumed to have three rings; hence, the parameters are noted with i = 1, 2, 3. The set of profile parameters that define the modal characteristics of the proposed FMF is [r1, r2, r3, Δ1, Δ2, Δ3].



(a) (b)

Figure 1 (a) Refractive index profile as a function of radial distance and (b) cross-sectional view of the proposed ring-core FMF.

Data Set Generation

In machine learning, the initial step involves creating a sufficient dataset to ensure accurate prediction of the desired parameters. The ring-core FMF parameters are adjusted to achieve the desired number of modes while minimizing coupling between neighboring guided modes. The finite element method (FEM)-based software COMSOL is used to input these parameters and find mode solutions [29].The data set is generated by altering the range of design parameters, resulting in a maximum of 26 modes over a broad range of neff values. The primary parameters are guided modes, whereas the secondary parameters are the difference between neighboring modes, denoted as Δneff [30] The structural parameters of the proposed FMF are determined by training the models to anticipate a specific value of Δneff. The ML models are trained using structural parameters as inputs and the effective refractive index (neff) as outputs. Over 50% of the mode solutions meet the weak mode coupling criteria. Table 1 Range of profile Parameters for the proposed three-ring-core FMF.

Parameters	**Minimum**	***Maximum***
r1[µm	0.5	*5*
r2[µm]	6.5	*11*
r3[µm]	10	*14*
Δ1[%]	0.002	*0.025*
Δ2[%]	0.006	*0.032*
Δ3[%]	**0.001**	***0.01***

The Machine Learning Process

The proposed FMF design process involves forward design and inverse modelling. The forward design creates a dataset for machine learning models, which creates a bridge between the desired

Outputs and structural parameters. The inverse design process is fast and accurate, with 70% of the data for training and 30% for testing. The model's profile parameters are predicted Fig. 2.

The inverse modeling, with the parameters chosen to minimize the error between actual and predicted values [1]

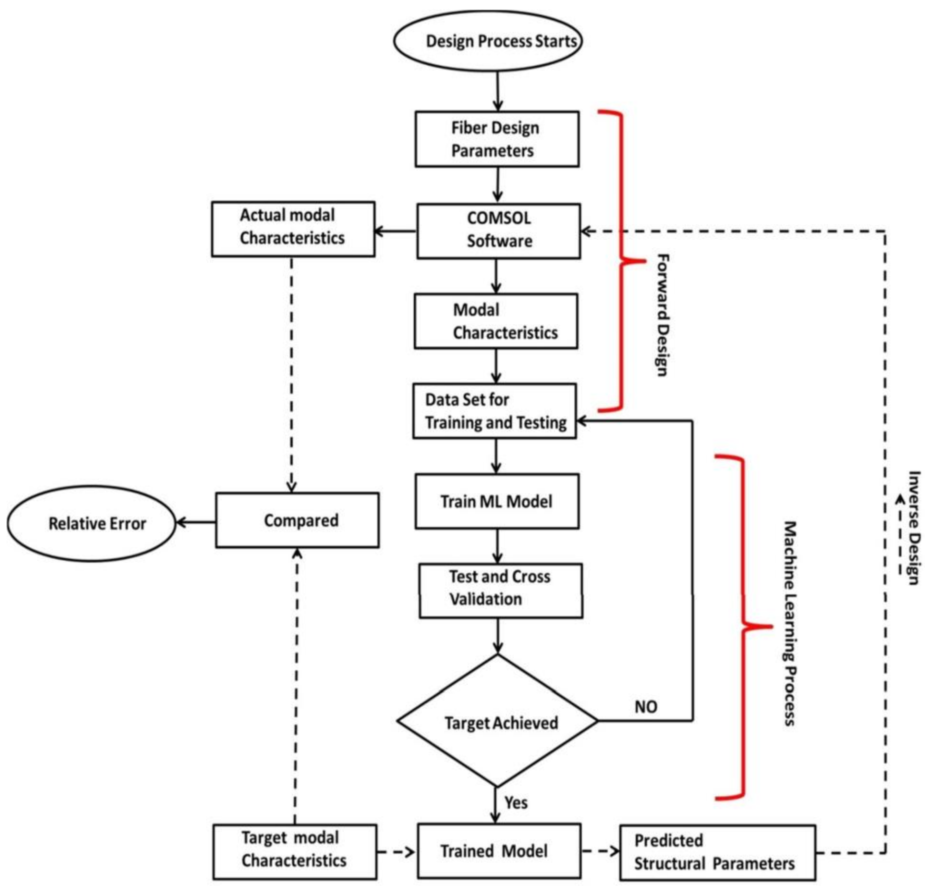


Figure 2 Flow diagram of the regression-based inverse design process for the RC-FMF [1]

Optimisation techniques for FMFs

Frequency Modulation philters (FMFs) are complex systems with a limited number of modes, making them difficult to optimize. Genetic algorithms (GAs) are suitable for multi-objective optimisation but have increased computational complexity as the number of degrees of freedom increases. Particle Swarm optimisation (PSO) is an alternative approach that uses simple mathematical rules to continuously modify positions in the search space. PSO is computationally more economical than GAs for continuous design variables but may be less accurate for complicated designs [31,32].

Deep Neural Networks (DNNs) can establish intricate, non-linear conations between inputs and outputs using a large dataset of training examples to learn and predict complex structures with multiple variables. However, the precision of DNNs is greatly influenced by the magnitude of the training dataset, which often requires significant physics-based simulations.

To minimize computational expense in deep neural network applications, various device-specific approaches have been developed, such as Generative adversarial networks for optimizing met gratings and Generative Inverse Design Networks (GIDNs)[33,34].

GIDNs significantly decrease the amount of training data needed to obtain high-quality designs by more than ten times in basic optimisation approaches that rely on gradients. Their active learning strategy involves systematically incorporating numerous designs close to optimal into the training set, surpassing conventional passive optimisation techniques with deep neural networks even when the amount of training data is greatly reduced [35-38].

Inverse design using deep neural networks

A deep neural network (DNN) that has been trained to analyses the structural characteristics of particular photonic systems can be employed to perform the inverse design of structures with predetermined qualities **(see Figure 3 a).** As a fundamental strategy, the weights and biases of the deep neural network (DNN) are immobilized once the training phase is over. Next, gradient descent is employed to iteratively adjust the configuration of the fiber by minimizing a freshly developed cost function (e.g., -Min|Δneff|, as demonstrated in [3].

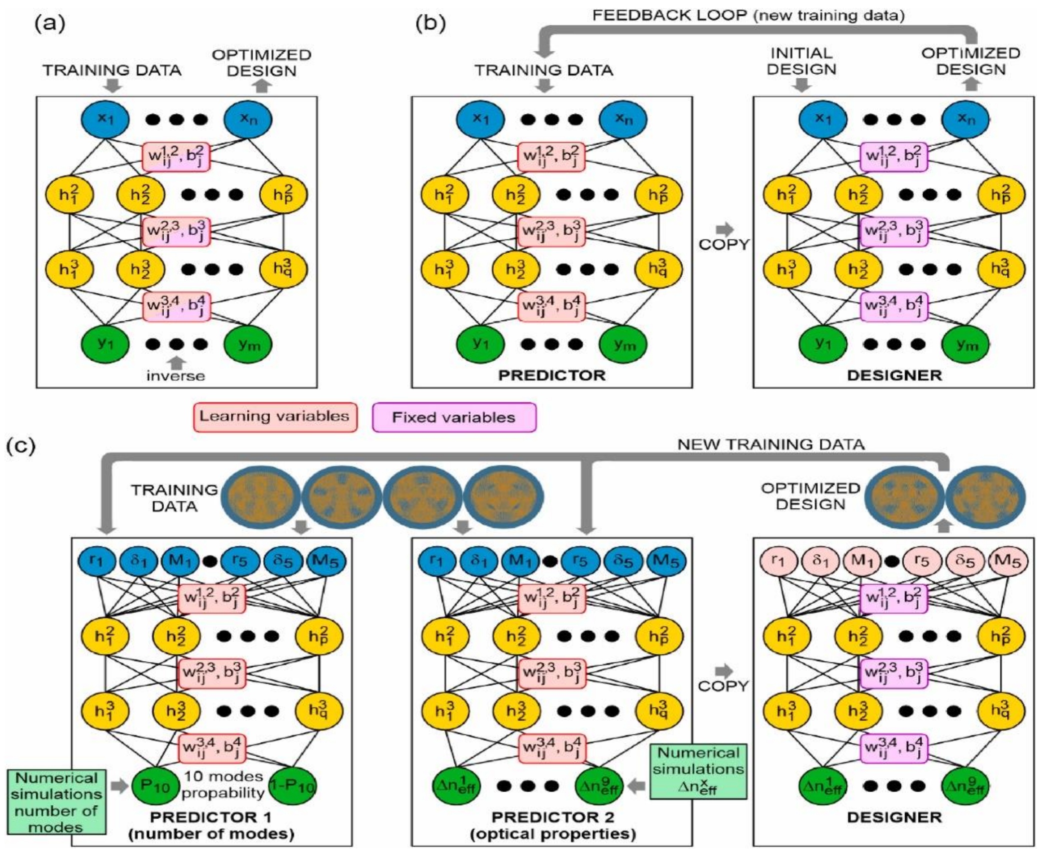
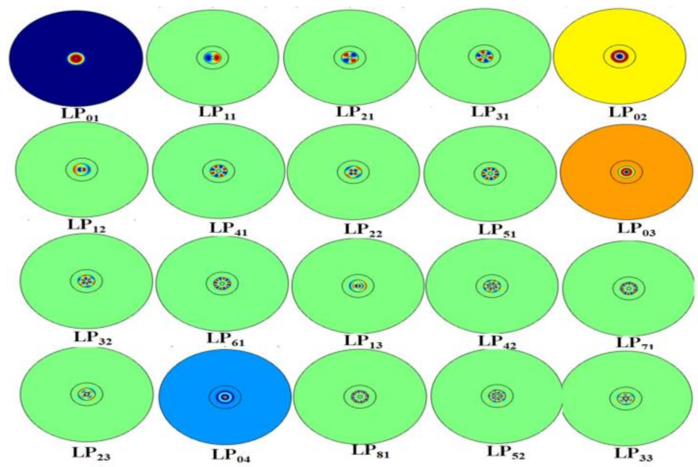


Fig. 4. Deep neural networks: (a) inverse design network (b) generative inverse design networks, and (c) proposed network[3]

Deep neural networks (DNNs) face challenges when trained on datasets with randomly generated fibres. Although they can predict outcomes for these fibers, they may not provide precise mapping for ideal designs. Expanding the dataset can improve DNN accuracy, but optimisation of high-performance designs is hindered by the lack of prioritization of ideal solutions and the time-consuming process of creating datasets using physics-based simulations. Gradient descent optimisation techniques can face obstacles due to local minima or other key points where the function's gradient diminishes. Although the Adam optimizer can alleviate issues with local optima, it is not entirely infallible in overcoming these hurdles [39,40].

Regression Model

This study uses regression models to correlate the secondary target (Δneff) with the structural properties of the proposed Fiber-Film-Film (FMF) structure. However, it does not demonstrate enhanced accuracy with a reduced number of training samples. Regression models utilised are ordinary least-square linear multiple regressions, k-nearest neighbor's of multi-output regression, and multivariate ID3-based decision trees. The decision tree (DT) approach is a supervised learning algorithm that is utilised for classification and prediction tasks. The system utilizes a hierarchical structure consisting of root nodes, decision nodes, and leaf nodes, all organized in a binary tree format. This study utilizes the ID3 algorithm, which employs a top-down methodology [41-45] The iteration process entails the start of entropy and information gain for attributes, the selection of attributes with the highest information gain and smallest entropy, the creation of a subset of data, and the execution of subset processing for new attributes. The Python platform is used for performing activities. The ten-fold cross-

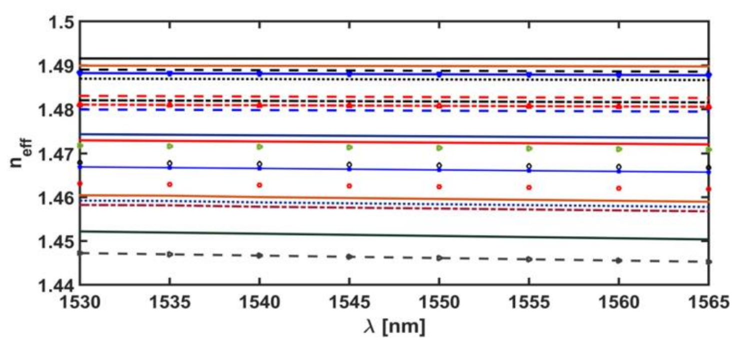


validation (CV) approach was employed to assess the accuracy and resilience of the models. A rotating sampling technique is employed to The Id3-based decision tree for multi-output regression was found to be the most reliable and accurate machine learning model for inverse modelling of FMFs. Inverse modelling through coupling optimization.(a)

select 30% of the data from the complete dataset,

showcasing the model's precision in describing structural parameters. The negative mean absolute error is used for assessing the CV score, where the model with the lowest CV score is the most reliable [24].

ML learning is a breakthrough for the fibre industry and can be used for other complex FMF designs with better weak



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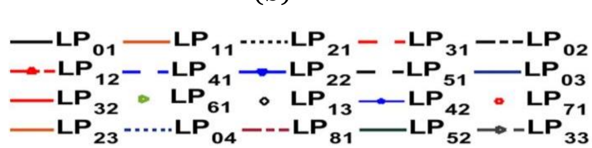


Figure 4 (a) Mode-field distribution at 1550nm and (b) variation of jeff as a function of wavelength over the C-band for the proposed twenty-mode 3 ring-core FMF.[2]

The proposed FMF design, which incorporates weak coupling optimisation, has been successfully designed using machine learning. This approach can be expanded to include factors like loss, dispersion, DMD, and effective mode area. The ML-guided FMF designs, which support 5, 10, 15, and 20 modes and exhibit weak mode coupling, are promising for future communication systems using direct-detection MDM transmission. The study also expanded to forecast profile parameters for a distinct RC-FMF to achieve weak coupling [46, 47].

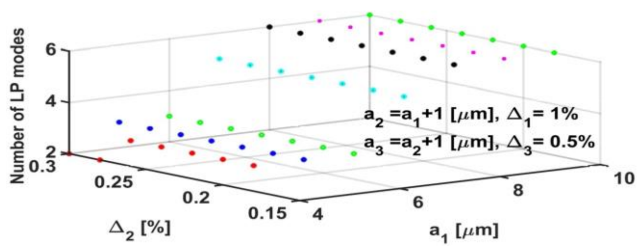
Extension of inverse modelling

The RC-FMF, a four-layer ring-core few-mode fiber, has a greater effective mode area (*A*eff) compared to the normal circular-core FMF, resulting in low transmission loss, minimum nonlinearity, and negligible micro-bend loss to forecast the profile parameters of this structure, an inverse design technique is employed. The fiber geometry is described extensively, confirming the strength and ability of the regression-based machine learning method [48].

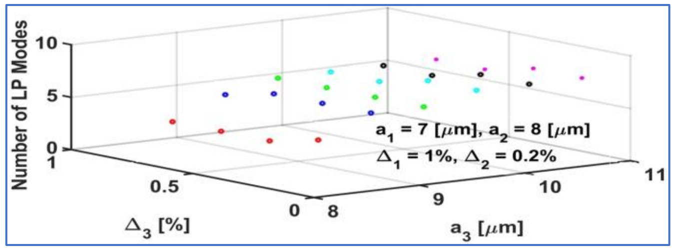
The design process for a weakly-linked four-layer ring-core few-mode fiber is conducted using the commercially available Opti-wave platform. The simulation of the proposed work uses Opti-fiber 2 and Opti-System versions. The sequence of actions required in the complete procedure includes generating a suitable dataset, selecting design parameters, and adjusting the design parameters to achieve a certain number of modes with little interaction among some adjacent modes. The values provided in Table 5.6 are used as input for the Opt fiber programmer to calculate the mode solutions (*n*eff) for each of the guiding modes. The mode solutions are organized in a 2000×17 matrix for training and assessment. The model is evaluated by assuming that 80% of the data is allocated for training and 20% for testing. The decision tree-based regression model was chosen above linear regression and k-NN-based regression for the multi-output regression model.

The decision tree model was determined to be the most accurate with lower error rates, facilitating the process of associating the secondary target (Δneffi = (neffi)__(neff(+1))) with the structural parameters of the proposed FMF[49].

In addition to DT, the proposed approach involves using linear regression and k-NN in multi-output regression models for RC-FMF. The task is completed using the Python programming language to demonstrate that DT offers the most accurate predicted parameters.



(a)



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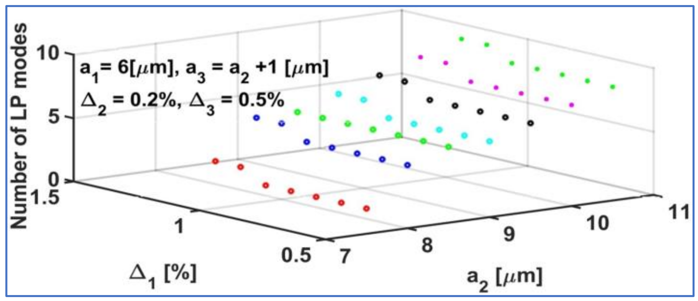


(c)

Figure 5 Number of LP modes through the proposed RC-FMF as function (a) $a1$and $\Delta2$, (b) $a2$ and $\Delta1$, and (c) $a3$ and $\Delta3$ at 1550 nm

Table 2 Range of profile parameters for the proposed RC-FMF to guide more than five to 10 modes

Parameters	$a1$[µm]	$a2$[µm]	$a3$[µm]	$\Delta1$[%]	$\Delta2$[%]	$\Delta3$[%]
Minimum	6	7.5	11	0.004	0.001	0.002
Maximum	10	12	15	0.015	0.005	0.01

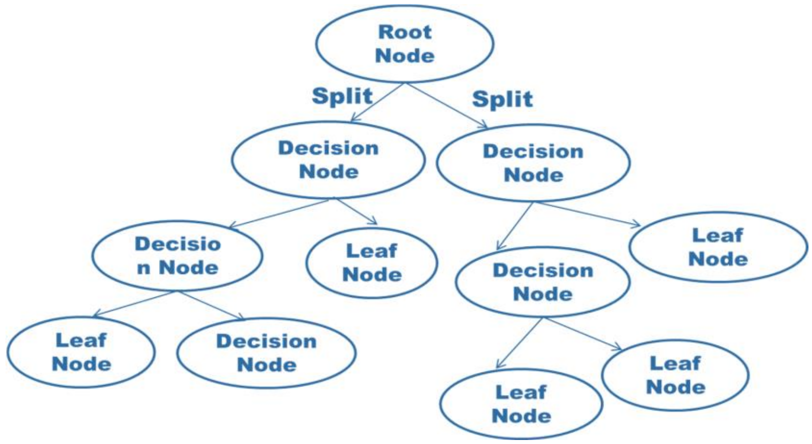


Figure 6 representation of the decision tree-based regression model. Through the ten-fold CV score, R2-score, and correlation coefficients.

An analysis was conducted to evaluate the precision and resilience of all three models. The results for each of the three regression models are presented and compared in Table 2. The findings indicate that the DT regression model is the most effective in predicting the profile characteristics of the proposed fiber. This conclusion is supported by a low CV score, high R2-score, and strong correlation coefficients. Error functions, such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), are employed to assess the performance of the models. These difference of $1.5 \times 10{-}3$ [50].

error functions are presented in Table 2. Figure 5 displays the real and forecasted results of the decision tree model across the data index for all six profile parameters to verify the precision of the trained model. The training dataset is defined as [$a1$, $a2$, $a3$, Δ1, Δ2, Δ3, $n$eff1, $n$eff2, $n$eff3, ... , . . $n$effM, M], where $n$effi represents the effective refractive index of the ith mode solution. This dataset is used for the M-number of modes. The dataset was generated with a minimum effective difference of $7.5 \times 10{-}4$ and a maximum effective

MDM Link Setup

The radial mode index of the RC-FMFs can be set to 1, which limits the number of modes in each high-order mode group to four. This reduces the complexity of MIMO (multiple-input multiple-output) systems and simplifies the reception of higher-order mode groups. As the azimuthal mode order of the ring-core FMF increases, the coupling between nearby mode groups decreases. This potentially makes ring-core FMFs usable in higher-order mode space. The proposed FMF has six distinct data channels and is constructed using intensity modulation and direct detection concepts. This allows for MIMO-free signal processing at the receiver end. The performance of the link is demonstrated using commercially available Opti-system software [3

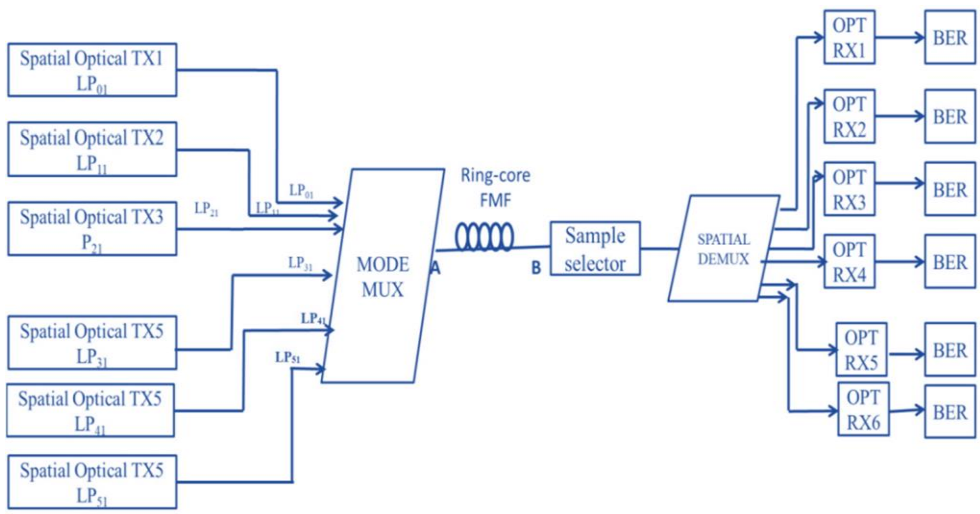
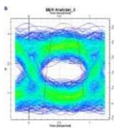
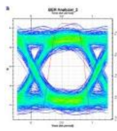
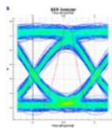
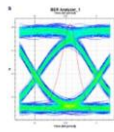
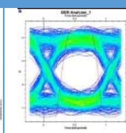
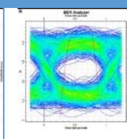


Figure 6 Weakly coupled MDM transmission link setup with the proposed inversely designed four-RC-FMF

The Multimode fibre (MDM) system was assessed using a connation length adjusted to 0.18 dB/km propagation loss. Demultiplexed outputs were detected using six-pin photodetectors with a receiver sensitivity of 18 dBm. A low pass philter (LPF) is implemented to mitigate modal crosstalk. The performance was measured by measuring the bit error rate (BER), received power, and maximum Q-factor at a wavelength of 1550 nm across a 50-kilometer distance. The BER performance varies from 10−39 to 10−9 over a distance of 10–50 km. Modes with less coupling exhibit superior BER performance. The four-RC-FMF architecture is used to transmit six modes, ensuring that the bit error rate (BER) for telecommunication applications remains below the permissible threshold of 10−9. The system operates over a distance of 50 km and achieves a data rate of 10 Gbps per channel [50].

Modes	**LP01**	**LP11**	**LP21**	**LP31**	**LP41**	**LP51**
EYE Pattern						
Min BER	4.45e-9	3.82e-11	2.82e-20	6.82e-21	5.82e-12	**4.12e-9**
Max Q-factor	5.1	7.09	68.56	9.34	7.19	**5.45**
Received power (dBm)	**-8.55**	**-6.31**	**-5.58**	**-4.45**	**-6.81**	**-8.45**

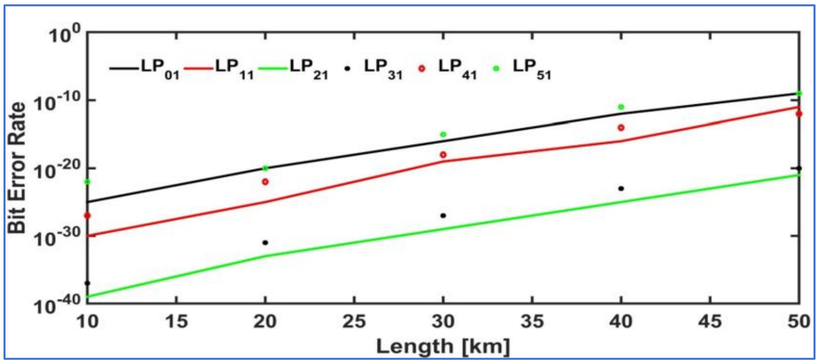
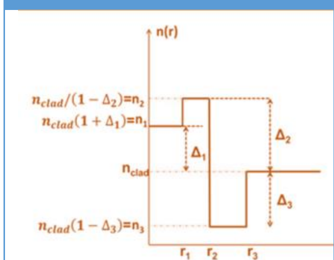
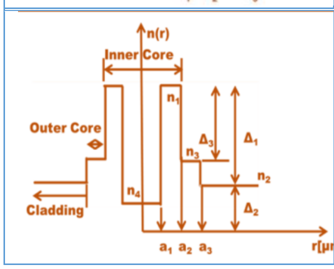


Figure 7 Link performance (BER versus link length) of the proposed inversely designed four-RC-FMF at 1550 nm

Result Conclusions

The ML-based regression models are used for the first time to perform inverse modelling of RC-FMFs. Three regression models are used to forecast the various profile parameters of the two types of RC-FMF structures. These models include ordinary least-square linear multi-output regression, k-nearest neighbors of multi-output regression, and ID3 algorithm-based decision trees for multi-output regression. The ring-core structures are chosen because of their superior qualities compared to alternative structures, as explained in the discussion. As the azimuthal mode order of ring-core FMF increases, the coupling between higher-order neighbouring mode group decreases. This property makes the proposed RC-FMF the most suitable choice for weakly coupled MDM systems. The decision tree for multi-output regression has been found to exhibit good accuracy for inverse modeling, compared to linear multiple regressions, k-NN regression, and the ID3-based decision tree regression model. Compared with linear regression, the DT model handles nonlinearity and collinearity more successfully. DT is a supervised learning algorithm, whereas k-NN is an unsupervised learning algorithm. The decision tree used for multi-output regression demonstrated a significant level of precision, with a correlation coefficient of at least 99% and a minimal relative error ranging from 10−3 to 10−4. The DT model predicts that the structural characteristics of the two types of RC-FMF will guide the 5, 10, 15, and 20 modes, respectively. The predicted parameters are subsequently used to construct the suggested FMF using COMSOL and Opti-fiber. This leads to the establishment of a 6 10 Gbps MDM system by intensity modulation and direct dictation, which is achieved by employing the inversely planned four-RC-FMF. The connation has been established across six spatial modes that are poorly interconnected. Table 4 presents a concise overview of the inverse modelling approach that has been addressed. Table 4 the inverse modelling of proposed RC-FMFs using DT-based regression models

This inverse modelling process through ML is universally applicable and can be extended further to optimize other parameters like loss, dispersion, DMD, and effective mode area. The dataset can be further modified and reusable for predicting more number modes.

Proposed FMF Structure	**Accuracy of ML model (%)**	**Relative Error $\|Target{-}Actual\|$ [$\times Target$100]**	**Maximum number of guided modes**	**Min Δneff**	**Max Δneff**
	99.9	10−3 to 10−7	20	1.01 × 10−3	**5.04 × 10−3**
	**99.5%**	**10−3 to 10−4**	**10**	**1.5 × 10−3**	**3.5 × 10−3**

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