DWDM reconstruction using supervised and unsupervised learning approaches

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This paper attempts to reconstruct and optimize a DWDM system by avoiding distortions such as Four-Wave Mixing (FWM) and high signal distortion due Inter-Channel Interference (ICI) using supervised and unsupervised learning approaches. FWM in high channel DWDM system reduces the network flexibility, transmission capacity and increases computational difficulties. The ICI and Signal distortion that affects spectral efficiency, increases network latency, leading to undesirable data re-transmission. To solve these above stated issues, the DWDM system necessitates optical variables optimization using supervised and unsupervised regression learning. In this paper, we reconstruct the DWDM system design using supervised and unsupervised regression learning approaches, which are used to identify, correlate, and optimize the FWM influencing optical parameters. Furthermore, trained datasets are generated from parameter-based simulations. Results are analyzed using supervised and unsupervised regression approaches, which improves the DWDM mechanism and achieves accuracy through a computerized regression model controller. Thus, the reconstructed DWDM system is re - designed with optimized FWM parameters obtained through supervised machine learning approaches, and unsupervised training evaluates the proposed R-DWDM system to predict Q-factor, OSNR, signal, and noise power levels accurately.

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1. Introduction

DWDM system in optical networks provides a high data rate for long-distance and ultra-speed transmissions. More data rate requirements with high network capacity introduce fiber nonlinearities, especially Four-Wave Mixing (FWM), in an optical DWDM network. In an optical fiber, the Propagation of two or more optical input signals in the same direction generates a new signal with sum and difference in their frequencies. As a result, the newly generated FWM signal can co-propagate with the input signal and causes more interference in neighbouring channels [1]. The occurrence of FWM in an optical DWDM system will cause signal distortion and introduces more cross-talk, which degrades DWDM network throughput and provides higher latency. Besides, parameters such as input power, channel spacing, fiber's core effective area, end-to-end transmission distance, data rate, and other fiber optic dispersive characteristics determine the occurrence of FWM in the DWDM system [2].

Many researchers proposes various methods and algorithms for analyzing and suppressing the FWM effects in DWDM design. FWM suppression is done through utilization of different dispersion characteristics of fiber such as non-zero dispersion shifted fiber, Reverse dispersion fiber, dispersion flattened fiber and highly nonlinear ultra-flattened dispersion shifted fiber (HN-UFF). The dispersion characteristics based DWDM design is complex in terms of structure and leads to minimum utilization of bandwidth [3]. FWM suppress through single mode fiber (SMF) and results in high dispersion effects in the receiver [4]. Furthermore, dispersion compensation fiber (DCF) method reduces FWM, whereas the method introduces more link loss long haul fiber optic DWDM system [5]. The CFBG method suppresses the FWM and disadvantage of this method is the wavelength time delay [6]. Moreover, less number of channel, for a distance of 100 km and low average Q- factor of 10.69 with minimal CFBGs investigate with high capacity DWDM system for efficient analysis [7].

Growth of demand over larger data rates with high capacity DWDM system introduces more complexity in design and affects the Quality of data Transmission (QoT). Therefore, we believe the conventional DWDM system combined with machine learning approaches will provide a practical design to reduce design complexity, accurately identifies the FWM influencing parameters through trained datasets, and improves QoT. The machine learning algorithms can provide more accuracy and shows the relationship between the optical input parameters. ML algorithms provide efficient design values for optical amplifier controls modulation format recognition, and optical performance monitoring [8]. ML technique is used to characterize and mitigate WDM's power excursion with 1% error accuracy [9].

Recently, in [10] regression based machine-learning approach is used to Predict the coupling length, effective index, and power confinement in nanophotonics waveguide analysis. Specifically, MLP regression provides 1-4% of error approximation in power confinements, 2% of error approximation in effective index, and shows perform better than other machine learning models. In [11] author discussed Logistic Regression, KNN, and ANN techniques to predict the QoT in terms of OSNR in the presence of EDFA power excursions and fiber nonlinearities. These techniques achieve above 70% of promising decision-making processes of control systems and require further analysis for physical layer features in the optical domain to identify the classifier's behavioural correlation level. In [12] Xiaoliang Chen et al. is experimented using supervised regression and classification module for the detection of anomaly in optical networks. Module presented in Xiaoliang Chen 2018 [12] achieves 99% accuracy in anomaly detection with 1% error rate and requires further investigation for diverse failure detection in the optical network. In [13] Shumingjiao et al. analyzed linear regression-based machine learning for blind image reconstruction in single pixal imaging (SPI) for an optical imaging system. In [14] Mirosław Klinkowski et al. proposed dynamic cross-talk optimization using regression learning for multi-core fiber in an optical network. The above regression learning technique provides flexible modulation format selection and achieves performance over various computationally expensive reference methods. Furthermore, Sanjaya Lohani et al. discussed CNN based prediction of output pulse propagation from nonlinear dispersive medium and dispersion characterization that simplifies the frequency scanning demonstration consumes more time and difficult to characterize in [15].

In the conventional DWDM system, identifying the FWM influencing parameters is done through iterative simulations, which affects the system accuracy and QoT. The iterative simulations for the effective design of DWDM fail to provide effective utilization of higher bandwidth, and data rate since the optical parameters in the device such as data rate, channel spacing, input power, modulation format, and optical gain are highly influencing FWM. The customized design of DWDM based on real-time environment is a challenging task. This paper proposed the supervised and unsupervised regression machine learning-based DWDM reconstruction, which reduces the FWM and improves QoT. Supervised regression-based DWDM system design avoids the considerable quantity of iterative calculations, which generally involves designing and testing an FWM parameters DWDM system. The proposed predictive modeling is customized based on identifying the optical independent and dependent parameters, which influences FWM in a fiber optic DWDM system. The independent and dependent parameters are classified based on R-value relations established between the optical parameters such as data rate, channel spacing, input power, modulation format, and optical gain. The rest of this paper is structured as follows. Section 2 discuss the literature works on FWM in fiber optic system design. Section 3 describes the simulation and process methodology. Reconstruction of R-DWDM design is presented in section 4. Some parametric discussion based on simulation results are presented in section 5. Comparison of simulated and predicted results are discussed in Section 6. Finally, section 7 sums up with the conclusion and future work.

2. Literature survey

The massive requirement of data rate in optical networks results in WDM implementation with spectral efficient parametric optimization. WDM technologies require accurate methods to reduce fiber nonlinearities and to meet increasing bandwidth requirements. In [16], Jagjit Singh Malhotra et al. is used optical phase conjugation (OPC) techniques, suppressed FWM power up to -20 dBm, which provides higher attenuation, and effectively mitigate FWM. In [17] R. Kaler et al. is discussed DWDM system design with low channel spacing and low input channel. Here the DWDM system design is confined towards channel capacity and bandwidth utilization. The author in [18] Jameel Ahmed et al. is presented FWM generation and enhancement parameters for a limited number of channels. However, in [19], Yaojun Qiao et al. is introduced a Gaussian noise model to understand the impact of nonlinear propagation in DMT that provides an accurate standard analytical model. The author in [20] Tonghui Liu et al. is performed an efficient FWM validation for channel spacing (0.1 nm) using DF-HNLF for short-distance communication.

In [21], Elham Nazemosadat et al. is discussed intra and inter-model FWM interaction in HN-FMF. The HN-FMF design with dual and 4-mode fiber achieves DMG of 0.2dB with 9.5dB minimal gain and DMG of 1.51 dB with 6.5dB minimal gain. Furthermore, in [22], Abhimanyu Nain et al. is analyzed the effect of FWM cross talk under ROF-WDM for different fibers. Here the optimization of channel spacing and input power for WDM system with LEAF is achieved. The author in [23] Sukhbir Singh et.al, is performed FWM suppression using optical phase conjugation modules in dispersion managed hybrid WDM-OTDM multicast overlay system. Although BER performance and coverage distance improved upto twice multiple factors, intricate system design affects WDM-OTDM performance. Critical characteristics of FWM is discussed in [24] Naif Alsowaidi et al. and performed FWM reduction using EOPM after the DWDM system. 64-channel DWDM based IM/DD achieved BER of 10-26 over 30 km and 70 km. In [25] Chiranjit Ghosh, et.al is discussed FWM suppression using LCFBG in the 22x 10Gbps WDM system and suppress FWM at a high input power of 10 dBm. The author Manisha Ajmani et al. in [26] presented FWM mitigation using a hybrid combination of DCF, FBG and OPC. The combination of OPC and DCF has an FWM suppression power of −135 dBm over 180 km distance.

The work in [27] D. Uzunidis et al. is performed an accurate validation through closed-form formula using QPSK modulation format in optical WDM design for less than 30 km span of fiber. Habib Ullah Manzoor et al. is analyzed FWM mitigation in [28] using Different modulation format and optical filter and achieves FWM efficiency of 25 dB. The author in [29] Tomas Huszanik et al. is mitigated FWM using the DQPSK modulation scheme for 32-channel Ultra-DWDM system design over 1250 km. In [30], T. Sabapathi et al. is also Mitigates SRS effect and FWM using WDM design with 0dBm input power and circular polarizers that consume high input power due to high spectral transmission. Kathpal et al. in [2] is Achieved 4dB FWM power for Channel spacing 75 GHZ with input source power 0dBm for 8-channeled DWDM. Optimizing parameters is carried out for a limited ROF channel. The author in [31] Jalil Aziz Hamadamin et al. is discussed the RZ-Modulation format to achieve Max Q-factor, low noise figure and low influence fiber towards nonlinearities. A higher data rate of 40Gbps per channel causes adverse effects such as high signal attenuation and dispersion effects. Obaid et al. in [32] is designed a DWDM system with 0.2 nm channel spacing, which provides more inter symbol interference (ISI) with 1.70 dB gain ripple and 4dB noise figure.

From related Works, we observed that the presence of FWM in high capacity DWDM system provides inter-channel interferences and causes more cross-talk, which affects network throughput and lowers energy efficiency. High channel DWDM consumes high power and introduces more signal distortions, which lowers DWDM system performance and increases computational complexity. Optimization of DWDM system parameters requires machine-learning techniques to predict FWM influencing parameters and improve data transmission quality. DWDM system is a general fiber optic dense wavelength division multiplexing system. Whereas, R-DWDM system represents a regression modelled controller based DWDM system. The aforementioned system is designed using the trained data set, which is obtained from field trials of optical DWDM network comprising of 'N' number of samples of the independent parameters and the corresponding dependent mitigating factors. The R-DWDM design tunes the parameters such as, channel spacing, bit rate, input power and optical gain after analyzing the behaviour of FWM according to the variations in its parameters.

This paper proposes a Regression-based DWDM (R-DWDM) system, which uses FWM influencing parameters, and the proposed system is trained through "N" number of an iterative dataset. We develop our methodology by modifying the DWDM network training stage to combine with supervised and unsupervised regression learning and shows the new predicted R-DWDM can reassign values of FWM influencing parameters to meet user requirements based on Q-factor, BER, OSNR, signal and noise power while being trained based on the iterative input dataset. This paper provides a simple, efficient structure of the DWDM system with High-level accuracy and reduces run computational time errors. Furthermore, the proposed system avoids more iteration and provides customized design based on real-time field requirements.

3. Simulation and process methodology

The Concept diagram for the proposed R-DWDM system design at different parameters are shown in Fig. 1. The optical system consists of WDM transmitter, WDM multiplexer, SMF, Optical amplifier, Dispersion compensation fiber, WDM demultiplexer, photodetector, Bessel LPF, and BER analyzer. WDM transmitter consists of the parametric configurations such as 10 Gbps data rate at input source, channel input power -10dBm (0.1mw), and channel spacing of 100 GHz NRZ Modulation format. The transmitter performs the modulation using Light signals for the input data sequences. The modulated data sequences from the WDM transmitter pass through the WDM multiplexer with channel spacing of 100GHz and Bessel filter, as shown in Fig. 1. WDM multiplexed signal transmit through the single-mode fiber (SMF) of length 100 km. SMF consists of parameters such as dispersion coefficient of 16.75 ps/nm/km, attenuation coefficient of 0.2 dB/km, dispersion slope 0.075 ps/nm^2/km, Beta$_2$ is -20 ps^2/km, differential group delay 0.2 ps/km and PMD coefficient 0.01 ps/sqr (km) are employed.

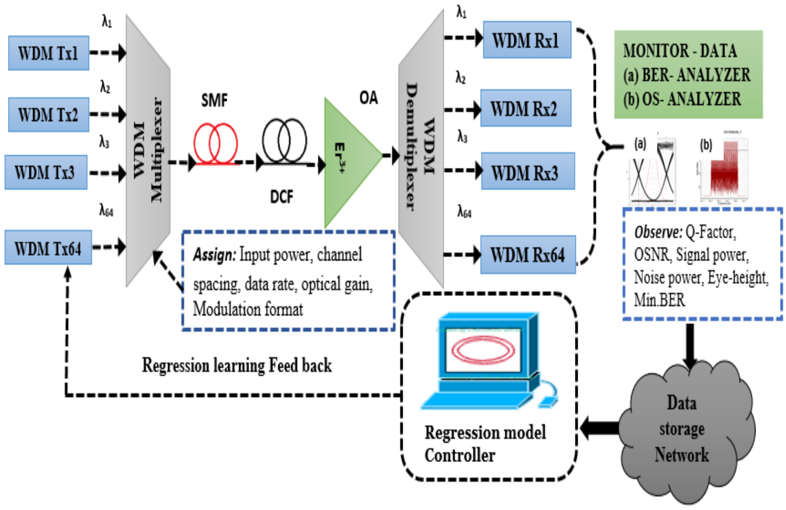


Fig. 1. Concept diagram: WDM Tx: Wavelength Division Multiplexer Transmitter, SMF: Single-Mode Fiber, DCF: Dispersion Compensation Fiber, OA: Optical Amplifier, WDM Rx: Wavelength Division Multiplexer Receiver, BER: Bit Error Rate, OS-Optical Spectrum (color online)

The signals from the SMF fed to the Optical amplifier for amplification with a gain of 20 dB. Further, the signal transmit through Dispersion compensation fiber (DCF) to avoid FWM losses. Then amplified signal transmit through the Dispersion compensation fiber of length 20.93km. The DCF consists of attenuation coefficient of 0.2 dB/km, differential group delay 3 ps/km and PMD coefficient 0.01 ps/ (km)^0.5. In the receiving end, the WDM demultiplexer receives the filtered signal from DCF for the demultiplexing signals. The demultiplexed signal transmit through photodetector for converting light into an electrical signal with dark current 10 nA, thermal power density 100e-024 W/Hz, and PIN Responsivity 1 A/W. The electrical signal transmitted through the Bessel LPF and received at the BER analyser.

The parameters such as optical gain, input power, and effective core size of optical fiber, channel spacing, data rate, and modulation format with different duty cycles vary to identify each parameter's optimized values. The iterations are performed through the OptiSystem.14 for FWM mitigating factors. BER analyser and optical spectrum analyser measures the values from simulations. Furthermore, the above-measured dataset is considered a trained dataset to regression controller, in which regression calculations are performed and provide R-values. The level of correlations are analysed through R-values that presents correlations among the FWM influencing parameters. Through this regression controller, mathematical equations are generated based on the dataset. We are generated data set from 100 simulative iterations by randomly varying the parameters, which influences FWM nonlinearities, and applied into a regression controller for efficient analysis of each parameter. This regression controller performs supervised regression learning and identifies the parametric values and their level of influencing FWM. These trained datasets are considered as input to the computer-generated regression controller.

4. Reconstruction of DWDM design

Fig. 2 presents reconstruction design of DWDM for parametric analysis. This is structured by analyzing linking, input, and output parameters discussed in the simulation setup. Reconstructed DWDM (R-DWDM) consists of independent input parameters such as data rate, channel spacing, input power, and modulation format. The dependent output factors in DWDM are Max Q-factor, Min BER, noise power, and OSNR that mainly mitigates FWM. More specifically, we train the proposed DWDM system to identify the FWM influencing parameters through a trained dataset, which is retrieved from various iterative simulations and performs regression learning.

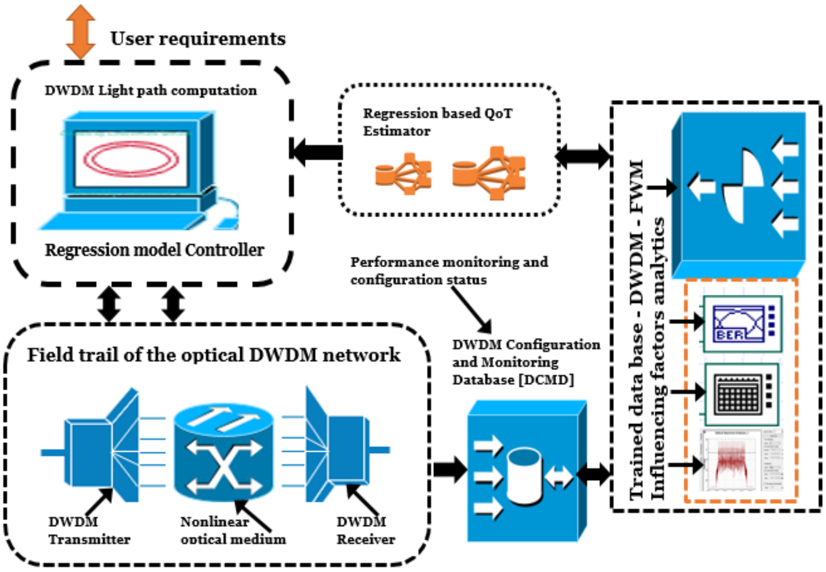


Fig. 2. Reconstruction schematic of Regression-based DWDM modeling (color online)

In the training procedure, we used a dataset obtained from "N" number of simulations and their associated FWM influencing (parameters) traces, where these traces serve as input parameters (to methodology), and the received outputs are compared with the (known) predicted dataset. Further, it allows the system to learn the DWDM system's structure and reconstruct itself to identify the factors, reducing FWM problem using R-values and its correlation levels obtained through mathematical calculations in advance. In regression model controller, DWDM field trial iterations are performed for different combinations of independent and dependent parameters and identify the strong correlation between the parameters through R-Value 0.8. The reconstructed DWDM system is used to predict crucial dependent FWM mitigating factors and analyze the effects of various FWM influencing parameters linked in the simulation setup.

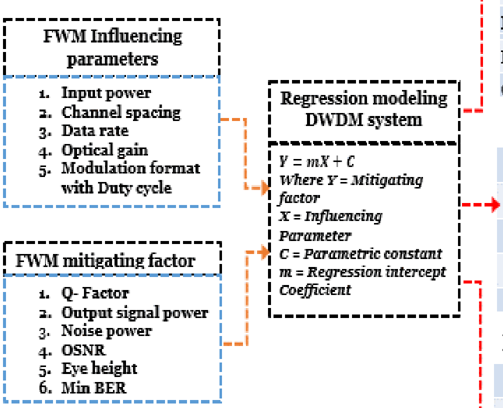
In DWDM light path computation, the regression model controller is trained based on user requirements. The R-DWDM design is to tune the parameters such as, channel spacing, bit rate, input power and optical gain after analyzing the behaviour of FWM according to the variations in the parameters. A trained data set is obtained from field trials of optical DWDM network comprises 'N' number of samples of the independent parameters and the corresponding dependent mitigating factors. DWDM configuration and monitoring database retrieve dataset from simulation setup and processed into the trained database section, which identifies and performs FWM influencing parametric analytics. The proposed Regression modeling develops the customized design of the DWDM system to meet real field user requirements

As we discussed in the simulation method, this method enables identifying FWM influencing parameters even from their low OSNR, Q-factor, signal and noise power. However**,** effective implementation of this method requires training the reconstructed DWDM system with more iterations, which consumes more time and introduces run time errors that affect system performance. To overcome this problem, we modify the learning procedure into a combination of supervised and unsupervised training. In Supervised Learning, the DWDM system is trained using a labelled dataset, which is already defined with optimized values to mitigate FWM. This labelled dataset can be compared with the training data set that can be obtained through N number of iterative simulations using design software. This learning approach learns from the training data and predicts the level of the outcomes for a futuristic dataset. Supervised learning approaches allow the system to produce and collect the data from previous experimentation runs. Furthermore, it helps to optimize the performance of the proposed system using the previous trained dataset to meet the real world requirements avoid the FWM issues.

Unsupervised learning approaches work with unlabelled dataset and it does not require any supervised approaches to monitor the system performance. In addition, we need to train the system to achieve optimized values of FWM mitigating factors as mentioned in a real time environment. Moreover, unsupervised learning approach helps to perform complex processing tasks, which involve multiple system parameters that are influential in the optimizing process of FWM issues. Unsupervised learning approaches help to analyze all the patterns in an observed dataset, and identify the features, which finally help to categorize the level of correlation. Since the experiment is performed in the real field environment, all the input parameters are analyzed and labelled using supervised learning algorithms.

In this research paper, both supervised and unsupervised learning approaches are discussed. Supervised learning helps in performing regression model controller and unsupervised learning helps to find out the grouping and associated level of correlation. In this procedure, prediction of FWM influencing parameters based on R-DWDM is trained on the simulated data. Here, the supervised regression procedure uses the previous Computer simulated dataset to help the R-DWDM system learn and identify FWM influencing parameters and improve system performance.

Moreover, the unsupervised training makes the proposed R-DWDM more specific in FWM problem identification. The combined procedure makes this method feasible and avoids a huge "N" number of iterations for the system during it's training stage. Furthermore, the unsupervised technique can be performed through the computer-simulated trained dataset**.** Finally, the reconstructed R-DWDM design is used to identify the FWM influencing parameters, determines the level of correlation for factors such as, signal and noise power, Q-factor, eye height to reduce FWM, and enhances system performance.



Regression modelling for 16 channel

Signal Power	1.0909 × (Input power) + 15.4109	0.9447
Quality Factor	: 14.3359 × (Duty cycle) + 30.5241	0.8710
Noise Power	1.0010 × (Optical Gain) + (- 69.8389)	1.0000
Eye Height	2.35×10^{-5} (Bit rate) + 10.259×10^{-5}	0.8784
OSNR	0.4159 × (Channel spacing) + 5.3782	0.8122

Regression modelling for 32 channel

Signal Power	1.000 × (Input power) + 16.3386	1.000
Quality Factor	0.29987 × (Channel spacing) + 0.4068	0.8605
Noise Power	0.998 × (Optical Gain) + (- 69.6024)	1.000
Eye Height	2.742×10^{-5} × (Bit rate) + 3.28×10^{-5}	0.9181
OSNR	0.4188 × (Channel spacing) + 4.9539	0.8147

Regression modelling for 64 channel

Signal Power	1.000 × (Input power) + 21.1632	1.000
Quality Factor	3.010 × (Optical Gain) – 20.2516	0.9699
Noise Power	1.001 × (Optical Gain) + (-74.4771)	1.000
Eye Height	8.053×10^{-4} × (Bit rate) + 0.0102	0.9481
OSNR	0.07188 × (Channel spacing) + 5.9921	0.8090

Fig. 3. DWDM Regression model with R-Values

This trained data set can be avoided after the learning process since the predictions to corresponding new independent parameters are computed only through the regression model controller learned parametric dataset. During the analyses, the relation between the various parameters, FWM and its impacts over the DWDM channel capacity and bandwidth stabilization is modeled through regression controller. The regression controller performs regression analysis to identify the dependent and independent parameters for an effectual DWDM output in the real field factors to mitigate FWM. The reconstructed DWDM model minimizes marginal error values based on a trained dataset of FWM influencing parameters.

Fig. 3 shows the calculations perform through regression modeling. For example, in 16-channel, the equation is $Output\ signal\ power = 1.0909 \times (inputpower) + 15.4109$ and R has 0.9447. Now the above equation studies the relation between the output signal power and input power through R-value. The R-value with 0.9447 shows the strong relationship between the input power and output signal power whereas, $\mathrm{OSNR}: 0.1887 \times (\mathrm{Input\ power}) + 52.3411$ and has R-value 0.4243 and proves less relationship between input power and output signal to noise ratio. Furthermore, the calculations for 32 and 64-channel configurations for various influencing parameters are also performed similarly, and correlations are observed through R-value.

5. Parametric discussion

Optimization of FWM nonlinear effects in DWDM system needs to be prioritized for enhancement of system performance. In this parametric analysis, FWM influencing parameters are fixed and linked to the DWDM system, which computes an output mitigating factor and allows the reconstructed DWDM system to predict the dependent factors' values based on a new set of optical input parameters. In this section, simulation for different configurations of the DWDM system with various arbitrary parameters is developed to understand the characteristics of FWM. An intensive study is carried out to identify and characterize FWM issues with multiple factors. The influence of FWM is clearly understood by analyzing factors such as Q-factor, BER, output signal and noise power, and OSNR.

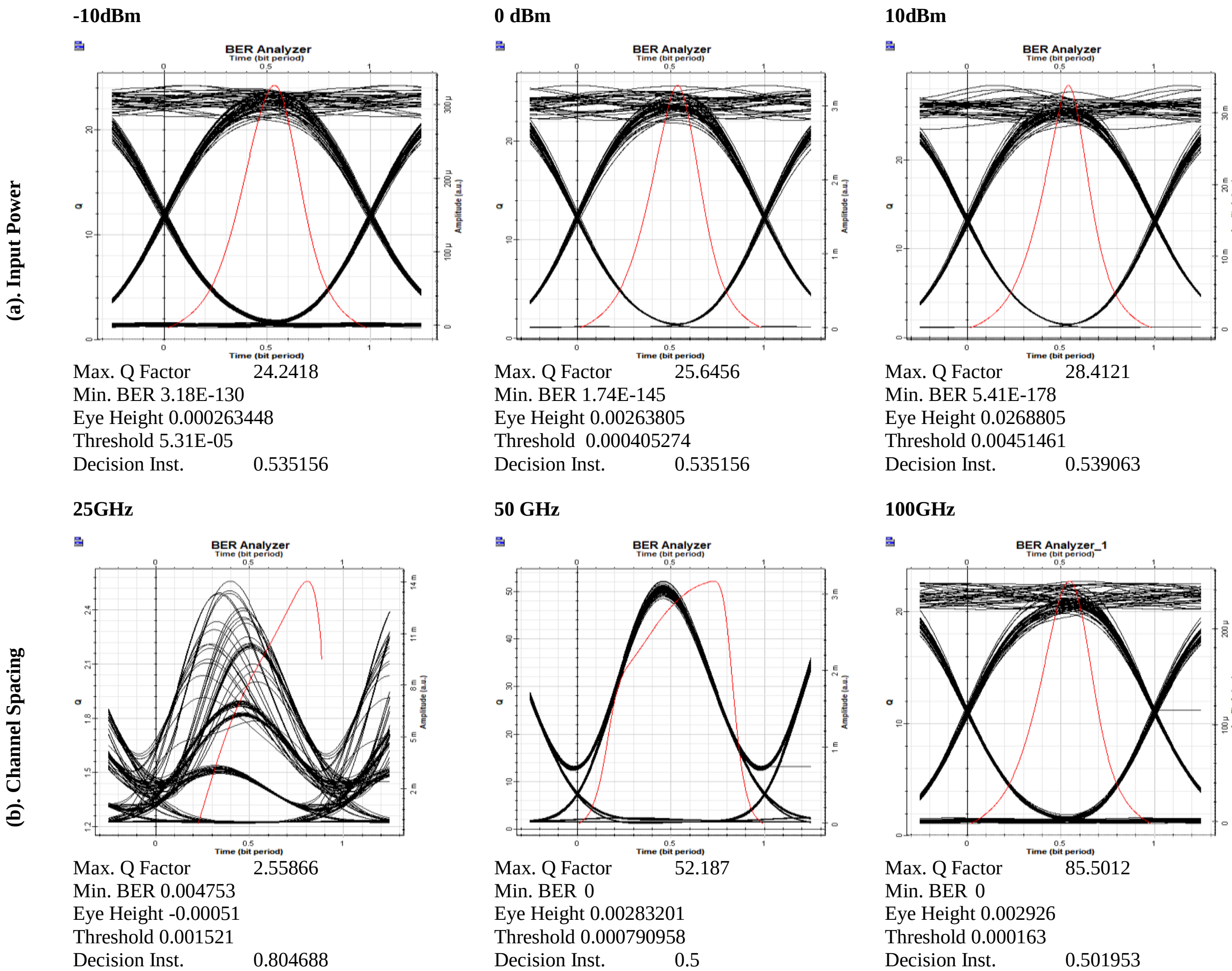


Fig. 4. Eye-diagram characteristic of varying (a) Input power and (b) Channel Spacing in DWDM system

Fig. 4 shows the eye diagram characteristic of varying input power and channel spacing, which leads to understanding their influence in FWM fiber nonlinearities. From the eye diagram, as shown in Fig. 4, results are observed for different channel sizes of a DWDM on an output spectrum analyzer. The iterative calculations for factors such as Q-factor, BER, and eye height understand the significant changes in dispersion. Lowering input power decreases output signal power, and hence OSNR decreases. From this analysis, lowering the transmitter input power reduces the FWM marginally. When input power goes low, there will be a prominent degradation of BER, eye height, and Q factor. From the estimated R-values, it is learned that a linear relationship exists between the number of channels in a system and output signal power, noise power, and eye height. The relationship is inverse for factors such as Q-factor and OSNR.

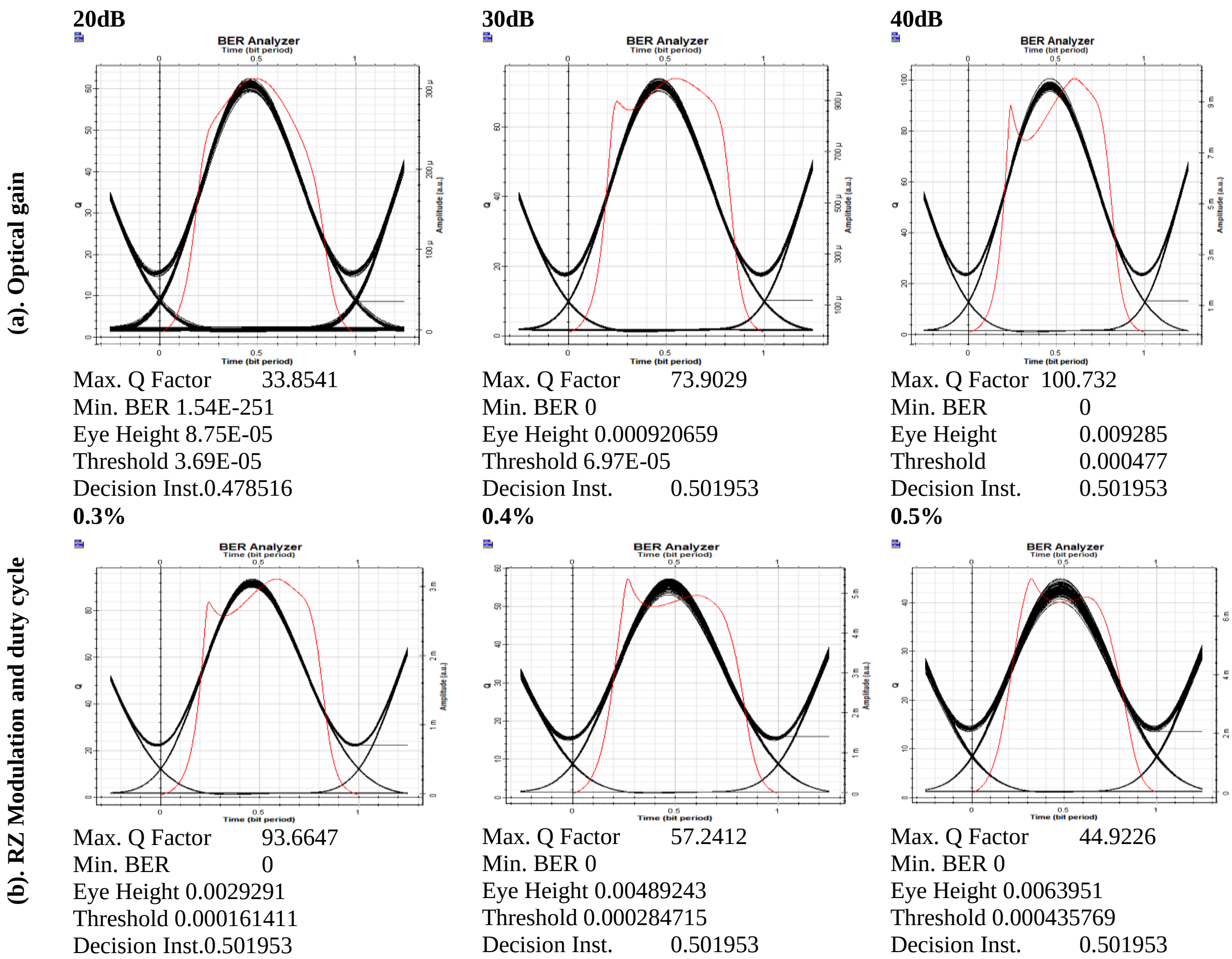


Fig. 5. Eye-diagram characteristic of varying (a) Optical gain and (b) Duty cycle in DWDM system

Channel spacing has an inverse proportionality relationship with the factors influencing FWM. Increasing the channel spacing minimizes the FWM effect and produces high BER and low Q-factor. The higher the number of channels, the higher is the interference between adjacent channels and results to elevate FWM issues. Low channel spacing in DWDM systems decreases Q-factor, increases noise power, and adversely influences OSNR. From the eye diagram, it is observed that lower channel spacing with high input power can accommodate more channels but at the cost of distorted eye characteristics. This validates the presence of more FWM effects are observed at narrow channel spacing (25GHz) and requires high considerations in a DWDM system. From the analysis, it can be studied that increasing channel spacing correlates positively to factors such as output signal power, Q-factor, and eye spectral characteristics resulting in reduced FWM. Increasing channel spacing will reduce noise power that will directly create a positive impact over OSNR. Fig. 4 shows the eye diagram characteristic for the factors obtained with different channel spacing for a 64-channel. It can be observed that the eye height is better when the channel spacing of 100GHZ. This results in a better Q-factor, but this is a trade-off parameter and needs to be decided based on the system requirements.

Fig. 5 shows the eye diagram characteristic of varying optical gain and Modulation format with duty cycle, which leads to understanding their influence in FWM fiber nonlinearities. Optical gain and output signal power are directly proportional factors that increase gain and good spectral characteristics and hence reduce FWM. This comparative study shows that gain of optical fiber varies from 20dB to 40dB, which determines the FWM problem in Optical DWDM system.

Detailed analysis of FWM nonlinearities using the regression controller improves higher optical gain, signal power, and provides a higher correlation to output signal power and noise power. The power of eye spectrum characteristics resulting in excellent eye-opening. It shows from the regression tabulation that an increased number of channels deals with the higher data rate, results in high FWM, and affects Q-factor for different optical gain values. From eye diagram spectral characteristics, it is observed that an increase in optical gain, which improves the power level of the DWDM spectrum, leads to a higher Q-factor along with dispersion effect. The dispersion effects introduce pulse broadening that lowers the Q-factor. Other parameters, such as output signal power, noise power, OSNR, and power spectral eye characteristics, are improved when the optical fiber's gain increases.

In this discussion, the modulation format changes from NRZ to RZ format and duty cycle is varied from 0.5 to 0.25. RZ-modulation format with 0.3% duty cycle provides very low BER and high Q-factor of 93.6647. This validates that for more channels with RZ modulation format and low duty cycle provides better results in-terms of Q- factor, BER. Spectral characteristics in eye diagram show minimum BER, leading to absolute data transmission, achieving very good Q-factor and increased eye height. This analysis concludes that DWDM system design with RZ modulation and low duty cycle provides a better reduction of FWM. Furthermore, it is also observed that increasing the duty cycle will lead to higher OSNR and affects the Q-factor of the DWDM system, which introduces more pulse broadening.

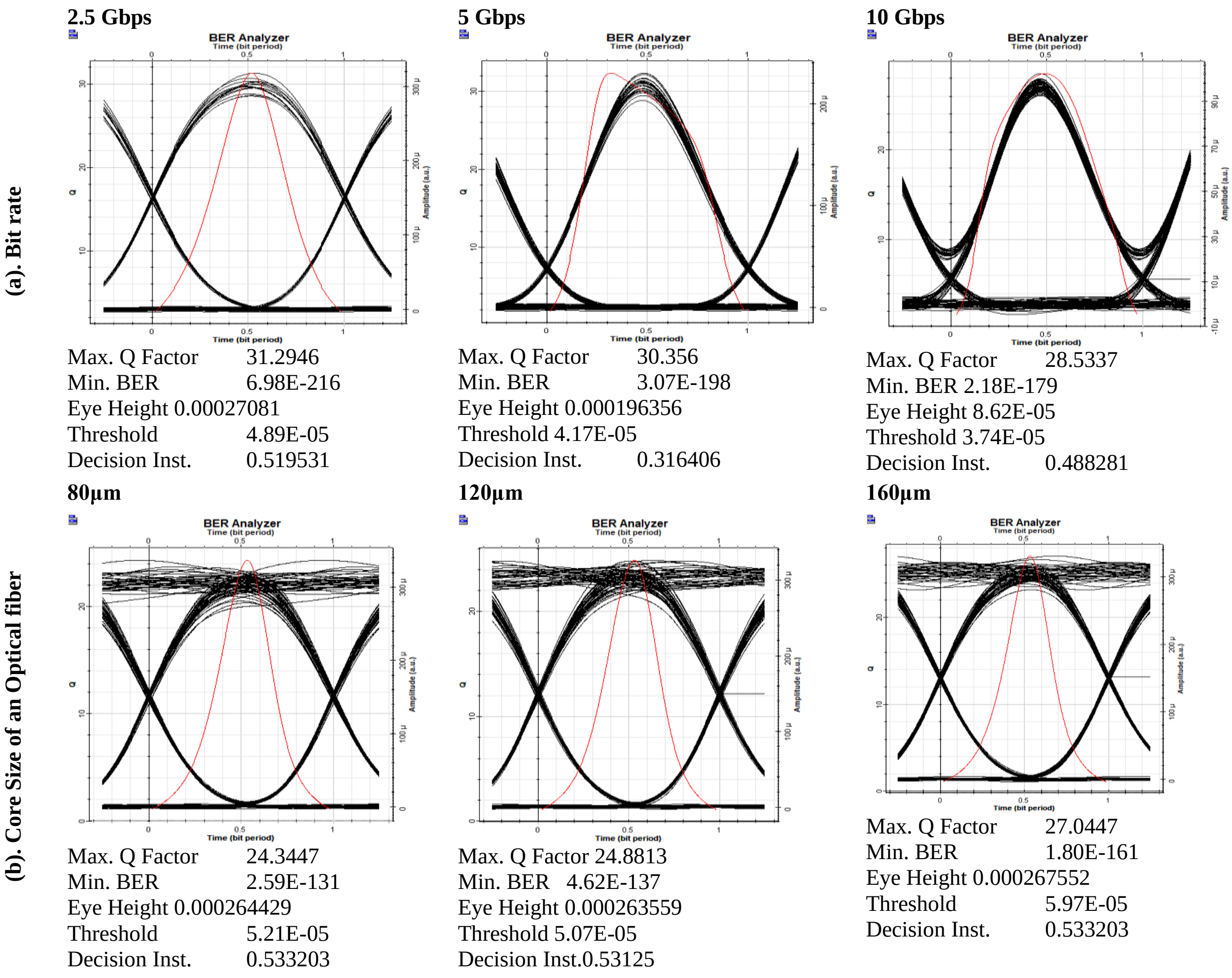


Fig. 6. Eye-diagram characteristic of varying (a) Bit rate and (b) Effective core size of an optical fiber in DWDM system

Fig. 6 shows the eye diagram characteristic of varying bit rate and effective core size of an optical fiber, which leads to understand their influence in FWM fiber nonlinearities. In this simulation, Bit rate is varied from 2.5Gbps to 10Gbps. Increasing bit rate, introduces more BER, which directly causes more dispersion in DWDM system. Nonlinearity factors such as noise power and OSNR are enhanced due to dispersion in DWDM system, resulting in decreased Q-factor. This analysis observed that noise power and OSNR show lower impact than the other factors such as output signal power, Q-factor, and Eye height characteristic. Since higher the number of bits transmitted for more channels with adequate channel spacing, i.e. 100GHZ, it will reduce noise power and OSNR produces excellent spectral characteristics. From Fig. 6, the Eye-spectral characteristic validates that a higher bit rate will introduce more noise in the DWDM system and hence reduces Q-factor. Furthermore decreases eye-height with more pulse broadening.

FWM characteristics are inversely proportional to the core size. From the simulation results, the enlarged core size of an optical fiber degrades FWM. By performing iterative analysis for different channel simulations, an increase in the effective core area (A_{eff}) decreases light intensity inside the optical fiber and degrades the FWM. An increase in LEAF of an optical fiber shows excellent eye-opening and achieves a narrow pulse. With adequate eye–height, the maximum Q factor of 27.0447 is achieved for a 32-channel DWDM system with 160um core size.

6. Comparison of simulated and predicted results

This section compares simulation and predicted results for the regression model controller using the regression algorithm. This leads to understanding FWM nonlinearity characteristics, identifies the influencing parameters, and provides correlations to their mitigating factors. The correlation factors will study the influencing parameters of FWM and find the level of input values for influencing parameters that reduce FWM. The analysis is carried out to identify and characterize FWM issues with multiple factors such as Q-factor, BER, output signal and noise power, and OSNR.

Regression model is an analytical method, which helps to study and find the relationship between the continuous variables. Here the linear relationship between FWM influencing parameters (X) and their corresponding mitigating factors (Y) are studied through regression model controller. The equation for the regression model is mentioned in the Fig. 3. Here, the mitigating factors such as Q-factor, noise power, eye-height, and signal power are considered as an output variable (Y) and FMW influencing parameters such as input power, channel spacing, data rate, and duty cycle are considered it as input variable (X). The regression intercept coefficient m is calculated from the regression algorithm through trained dataset.

From the regression controller, R-values are calculated, which provides the correlation and shows how the factors such as BER, OSNR, Q-factor, spectral characteristics are related to the arbitrary parameters such as, optical gain input power, bit rate, channel spacing, duty cycle and core size of optical fiber. Henceforth the term "factors" is used for max Q-factor, minimum BER, output signal power, noise power, and OSNR, and the term "parameters" is used as optical gain, input power, bit rate, channel spacing, duty cycle, and core size of optical fiber. The calculated R-value and the correlations are classified as shown in Table 1.

Table 1. Correlation levels of estimated R-values

S.No	R-value	Level of Correlation
1.	$1 \geq 0.8$	High
2.	$0.7 \geq 0.5$	Moderate
3.	$0.4 \geq 0.3$	Low
4.	$0.2 \geq 0.1$	Very low
5.	$R\ value\ is\ negative$	No

More than 100 Iterative simulations are run in this setup by randomly varying parameters for each of the different factors and calculated the R-value through regression modeling. For example, a simulation setup for a 64-channel DWDM system is developed in OptiSystem. FWM influencing (Input independent) parameters such as Channel spacing varies from 25 GHz to 100 GHz, and results are observed for the dependent factors. Results are tabulated as in Table 2.

Table 2. Simulated dataset of 64-channel for regression modeling under different channel spacing

Channel spacing (GHz)	Signal Power (dBm)	Noise Power (dBm)	OSNR (dB)	Max Q-factor
25	11.17792	2.357671	8.820248	2.55866
50	11.16735	-0.5234	11.69075	52.187
75	11.1587	-0.46419	11.62289	76.8309
100	11.16089	-39.4667	50.6276	85.5012

The regression equation is developed for the R-DWDM system based on Table 2. The channel spacing of 25 GHz for 64 channel has -1.251×10^{-5} × (Channel spacing) + 11.2381 and R-value 0.8943. From the Table 2, the channel spacing and output signal power are correlated with the above equation. The relationship between channel spacing and output signal power is strong because R-value is 0.8943. The regression model equation applied for various channel spacing, and output signal power to predict the results without simulation, and the same is shown in Table 1 as predicated value. Similarly, the predicted value is also verified for accuracy after simulating the same parameter, which is given as an input to the regression equation. The R-DWDM design for identifying and reducing FWM issues involves two training process stages. In the first procedure, we are training the DWDM system to identify the FWM influencing parameters using supervised regression learning on a trained dataset created for the training purpose. In the Second method, we use the proposed R-DWDM system to overcome FWM issues after being trained by iterative data. To achieve that, we perform an unsupervised training stage procedure, which learns to use a computer-generated dataset and measures OSNR, Q-factor, BER, Signal, and noise power to reduce FWM. In the first procedure, which uses a simulation-generated dataset for training, the regression modeling is performed for various parameters. Through regression, we predict the values of OSNR, Q-factor, BER, signal, and noise power, which determines the power level of FWM, and identifies their mitigating level. This shows that the R-DWDM is trained on experimentally measured data to identify the measurements of FWM influencing parameters and determine the marginal values to reduce FWM. However, this requires more than "N" number of iterations in the training stage**.** In the second method, the problem can be solved through combining the regression learning from simulated data with an unsupervised procedure, here we developed a mathematical relationship between the dependent and independent parameters and obtained R-value. We trained the R-DWDM system to predict the values of Q-factor, OSNR, BER, eye height characteristics, signal and noise power without performing any iterations through these R-values and mathematical calculations. As shown in Fig. 2, the R-DWDM system was trained using a combination of these procedures and identifies better values of FWM influencing parameters to reduce FWM issues. Using both procedures together, supervised regression trains the DWDM system to identify the values and deal with user requirements. The unsupervised method trains the R-DWDM system to determine the values of OSNR, Q-factor, BER, eye height characteristics to reduce FWM effects. Furthermore, we observed that the unsupervised method could not perform well without the previous one i.e., supervised regression learning. Fig. 7 shows the comparison of simulation and regression-based predicted results for different configurations of the R-DWDM system. Considering the larger dataset, which retrieves from regression model and an iteration results from conventional methods, it has a greater impact on the R-DWDM system design, which is illustrated in Fig. 2.

We use the regression-based machine learning method to optimize the FWM influencing parameters and get the optimal FWM mitigating factors' optimal value through R-DWDM design when the R-value reaches the minimum.

To understand the relationship between FWM influencing parameters and FWM mitigating factors such as OSNR, Noise power, received power, and Q-factor to estimate accuracy, we treat the more sample data according to the number of iterations. Through the conventional simulations and Regression model based dataset by converging the average estimation of mitigating factor values are calculated and mapped with simulated and prediction results graph, as shown in Fig. 7. The following simulation results are obtained by the random selection of FWM influencing parameters. The training set, testing data perform cross-validation, obtain the average results to ensure the proposed R-DWDM system model fits and trains the test data well.

From the predicted and simulated results, the parameters such as optical gain, input power, data rate, channel spacing, and the optical fiber's core size are highly influencing FWM in DWDM design. It can be confirmed through the obtained higher correlation level of these parameters for various mitigating factor such as Q-factor, OSNR, noise power and received power. In duty cycle calculations, which have a lower impact on FWM issues and achieves low correlation level and deviates from the prediction plot. From Fig. 7, it is observed that except duty cycle remaining parameters achieve the high-level accuracy with regression-based predicted results and simulated results. It is considered that the equal number of sample training data set for all the parameters, which influence FWM and determines the accuracy level of the predicted results. It can be observed that the complexity of the DWDM system and modelling time depends on the number of FWM mitigating factor with the sample-trained dataset.

Therefore, regression modelling predicts the FWM influencing parameter with high accuracy under the complex DWDM structure compared with regular iterations. The low R-value is obtained for duty cycle calculation, which does not lie in the estimation level and shows high deviations in their simulated and predicted regression results. In the future, we investigate more real time challenges in FWM analysis using the proposed R-DWDM design. Initially, we increase the methods and components involves in FWM analysis to generate mathematical modelling through regression learning, which includes as many spectral characteristics in the trained dataset. Besides, the proposed system is to be trained through many iterations, which leads the system to achieve extreme accuracy.

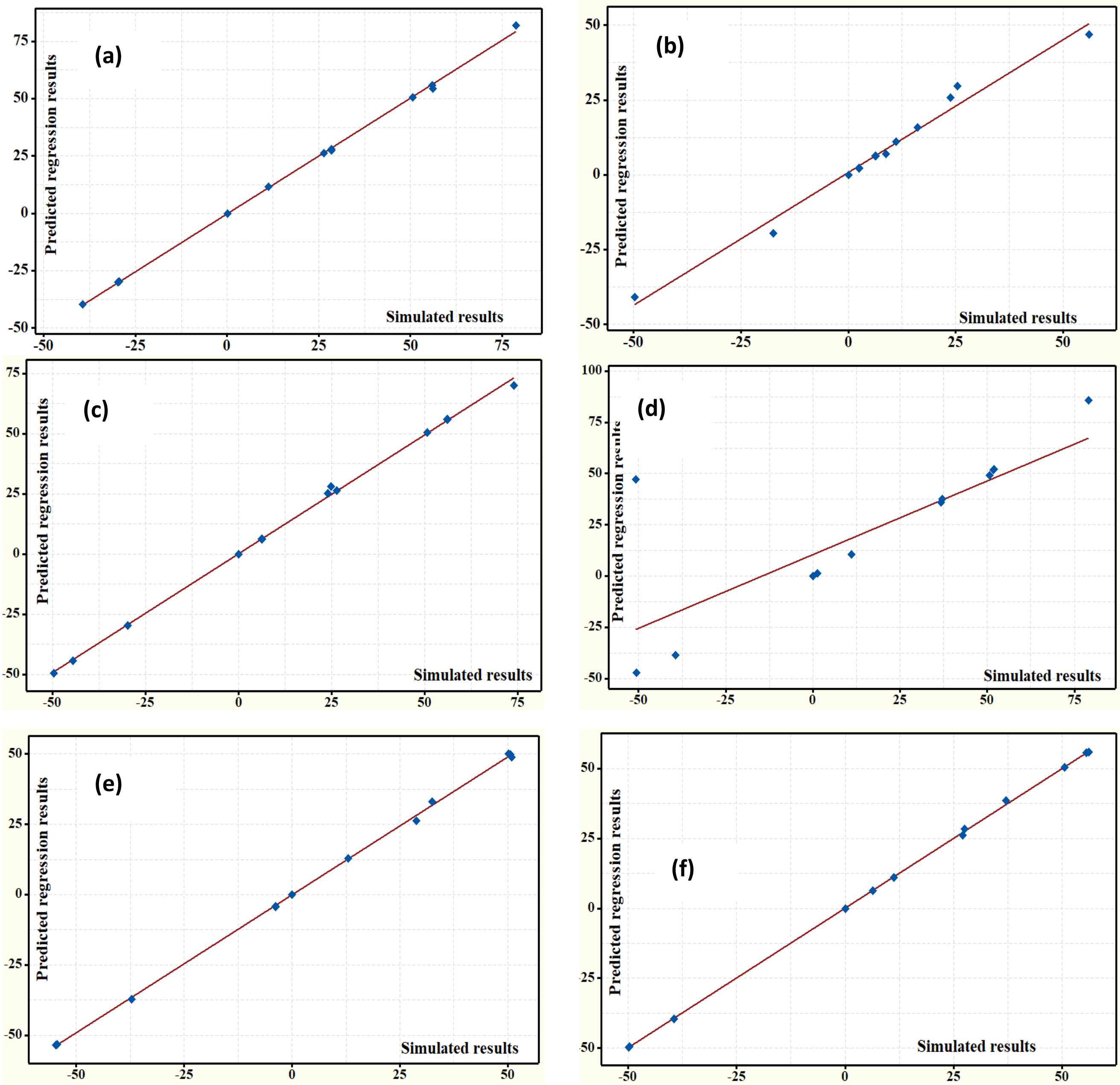


Fig. 7. Simulated vs Predicted results for (a) input Power (b) channel Spacing (c) optical Gain (d) duty cycle (e) data rate and (f) core Size (color online)

Thus, the proposed system achieves the FWM optimization by designing the DWDM system with -10dBm as input power, 50GHz as minimal channel spacing, RZ modulation format with 0.3%duty cycle, 10GBps as higher data rate with 80um as effective core area. At -10dBm input power optimized Q-factor of 24.2418 and BER of 3.18E-130 is achieved. Optimized minimal channel spacing of 50GHz provides Q-factor of 52.187 with very low BER data transmission. The proposed R-DWDM with 20dB optical gain obtains optimized Q-factor values of 33.8541 with Minimum BER of 1.54E-251. Furthermore, RZ modulation format for long haul transmission achieves Maximum Q- factor of 93.6647 and supports error free transmission. In the presence of 10gbps data rate the proposed system design achieves Q- factor of 28.5337 and Min. BER 2.18E-179. Choosing effective core size area as 80um provides Q-factor of 24.3447 with Min. BER of 2.59E-131 and shows the proper eye opening as shown in the eye characteristic diagrams.

7. Conclusion

In this work, we presented a supervised and unsupervised regression learning approach to reconstruct the fiber optic DWDM system to reduce nonlinearities such as FWM and high signal distortion with ICI. Parameter-based simulation is performed, and the obtained results are analyzed using supervised and unsupervised machine learning approaches. The supervised regression algorithm generates established correlations among the parameters and provides a firm idea of handling the FWM issues. Trained datasets are developed through supervised regression learning, which identifies the independent optical parameters such as Modulation format, optical gain, bit rate, channel spacing, effective core size of an optical fiber, input power, and the dependent factors such as Max Q-factor, Min. BER, noise power, output optical power based on natural constraints. Finally, an unsupervised learning approach is presented, using the trained dataset from supervised learning and improvising the proposed system to identify the FWM problem. Thus, unsupervised training makes the proposed R-DWDM system accurately predict Q-factor, OSNR, signal, and noise power levels. It is mandatory to consider all these parameters to achieve optimized Q-factor, Min. BER, and required output signal power. However, the parameter values are defined according to the practical requirements of data transfer in day-to-day applications. In general, repeated iterations of the simulation need to be performed for reduced noise, high signal distortion, and monitors FWM. These iterative simulations consume more run time and are prone to human errors, which can be avoided through supervised and unsupervised approaches. Comparing the predicted and simulated results show that the reconstructed DWDM system's accuracy level provides a real trade-off between various parameters that influence FWM nonlinearities in the fiber optic R-DWDM system. Furthermore, the future scope of this research paper will be an extension with combinations of various parameters, which influencing FWM with more dependent and independent variables through multiple regression methods.

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