Supervised regression modelling for mitigation of four-wave mixing in dense wavelength-division multiplexing systems

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Abstract. A recent global crisis associated with COVID-19 has encouraged millions of people to work from home, thus causing a drastic increase in overall network traffic, data-rate requirements and end network capabilities. This has also produced more noise, cross-talk and undesirable optical-fibre nonlinearities, especially a four-wave mixing (FWM) effect that deteriorates performance of dense wavelength-division multiplexing (DWDM) systems. A presence of FWM in the DWDM systems imposes increasing complexity and latency of networks, and decreases their spectral efficiency. In its turn, this degrades efficient utilization of optical bandwidth. To mitigate the above problems, we suggest a supervised regression modelling (SRM). A relevant SRM-DWDM approach performs self-parametric optimization of the DWDM systems with machine-learning techniques and finds real trade-offs among various factors that affect the FWM. Our model reduces *complexity of modelling* and computational time, *resulting in* accurate and reliable prediction of parameter values. We also evaluate the performance of our SRM-DWDM technique by comparing its data with the iterative results obtained for different parameters (e.g., output signal-to-noise ratio, Q-factor, signal power and noise power). Finally, we specify the procedures necessary for global optimization of DWDM systems.

1. Introduction

Fibre-optic systems with dense wavelength-division multiplexing (DWDM) provide high transmission capacity, wide bandwidth and efficient use of bandwidth [1]. Now it is important to ensure high reliability of DWDM systems to achieve high-quality data transmission in long-distance communication networks [2]. Increasing number of channels in a DWDM system makes its structure more complex and produces a number of linear and nonlinear issues [3]. One can mention in this relation nonlinear light scattering, Kerr nonlinearities and parabolic nonlinearities, along with amplified spontaneous emission. Moreover, there are such effects as stimulated Raman scattering [4], four-wave mixing (FWM) and cross-phase modulation [5], which also affect data transmission and optical signal-to-noise ratio (OSNR) in long-haul fibre-optic systems [6].

A presence of FWM in an optical DWDM system can affect notably the quality of signal during its transmission. Various parameters such as OSNR, bit-error rate (BER) and Q-factor are helpful to determine the effect of FWM and its influence on the system. Mitigation of the FWM in

DWDM systems [7] has been discussed in relation to various system functions such as number of channels [8], bit rate [9], channel spacing [8], modulation format [9] and duty cycle [10]. The influence of FWM in many waveguide devices is observed while varying pump power and detuning light wavelength [12]. A reduction of FWM achieved using different modulation formats in long-haul DWDM transmission systems has also been discussed and the system performance has been evaluated basing on the OSNR, the Q-factor and the BER [13]. A turn-to-zero (RZ) modulation format has proven to be less affected by the nonlinearities. It can provide a better Q-factor, lower distortion and lower noise [14]. Analysis of optical amplifiers for the DWDM systems under conditions of different channel spacings, input powers, optical gains and optical-fibre core sizes has provided estimation of such system factors as BER, Q-factor, OSNR and output signal power. This also yields in quantitative measures for the nonlinearities and cross-talk and predetermines the final values of guaranteed quality of transmission [16, 17].

Traditional methods employed for calculating optical networks require much time and increase system complexity, which hinders their use while achieving global optimization [18, 19]. These limitations can, in principle, be overcome with novel approaches, e.g. the techniques based upon artificial intelligence and machine learning (ML). The latter can provide superior solutions in relation to the complexity issues [20]. Detection, identification and management of failures in optical networks have already been studied using the ML techniques [21]. An ML-based reduction of OSNR, input power and noise figures and estimation of the quality of transmission in the DWDM networks have been discussed in Ref. [22]. The ML procedures and their efficiency for various communication fields such as software-defined networks [23], Internet of Things [24], wireless sensor networks [25], cognitive radios [26], wireless networks [27], computer networks [28] and traffic classification [29] have been studied.

One can outline the following problems to be solved in this direction: (i) design of long-haul optical DWDM systems with wider bandwidth and larger number of channels, which involves complex-network management and difficulties in collecting data from enormous number of monitoring points, and (ii) parametric optimization for mitigating fibre nonlinearities, especially the FWM effect. Sometimes these problems represent real challenges and cannot be easily solved through simple iterative simulations under diverse practical constraints. Therefore, a real-time environment requires efficient ML-based prediction approaches for self-optimization of high-capacity DWDM systems, following from user requirements, efficient network management and avoiding of bandwidth crunch.

In this work, we suggest a self-parametric optimization via an ML-based supervised regression model (SRM) for a high-capacity DWDM system in the presence of FWM. A so-called SRM-DWDM technique is designed and verified. It achieves higher data rate and provides better understanding of the parameters that influence the FWM. The suggested SRM-DWDM method is analyzed for various FWM-influencing parameters such as input power, channel spacing, modulation format, data rate and gain of optical amplifier. The final aim is user requirements of larger bandwidth and efficient utilization of channel capacity. These tasks can be performed under conditions of reduced system complexity and acceptable iterative runtime.

The article is organized as follows. Section 2 discusses in detail the related work on the subject. Section 3 provides the fundamentals of FWM and its influence on the DWDM systems. In Section 4 we describe a conventional (iterative) simulation setup for DWDM systems. Detailed information on our SRM-DWDM approach and the processes involved in its operation is gathered in Section 5. In Section 6 we report on the tests of our SRM-DWDM system and parametric

observations of various system functions and factors mitigating the FWM effect. Finally, Section 7 concludes and discusses a future scope.

2. Related work

There are several nonlinear impairment factors that deteriorate the efficiency of DWDM due to their uncertainty. To estimate these uncertainties, the quality of transmission and design considerations must be considered. The design considerations derived from either a simple analytical model or an advanced DWDM-designing techniques can be used. Channel spacing, modulation format, input power, data rate and some other influencing parameters are required to estimate the quality of transmission through a DWDM system. The introductory studies have shown that such parameters such as the OSNR, the noise power, the signal power and the Q-factor reveal exponential dependences on the channel spacing, the input power and the modulation format at high data rates. For example, Ref. [22] mentions fluctuations in the quality of transmission that affect the spectral characteristics and thereby introduce deviations in the optimal values of FWM-mitigating factors.

The authors [7] have analyzed a case of low channel spacing and small number of input channels, when the utilization of bandwidth and the channel capacity are limited. In Ref. [8] it has been shown that a larger number of channels (a case of 80 channels) and ultra-narrow channel spacing (0.25 nm) make the design much more complex. The work [6] has discussed a DWDM system with chromatic dispersion, which achieves 1.28 Tbps data transmission with some limited factors such as channel spacing and transmission distance. Unlike this work, a 0.2 nm channel spacing with high inter-channel nonlinearities has been analyzed in Ref. [17]. It can achieve the gain ripple 1.70 dB and the noise figure 4 dB. The author [3] has suggested a radio-over-fibre system, where optimization is achieved using an 8-channel WDM transmitter, a 75 GHz channel spacing, a 0 dBm input power and a 4 dBm FWM power. Different modulation formats with variable duty cycle for various channel spacings in an EDFA structure have been discussed in Ref. [10].

The work [1] has studied different FWM-influencing parameters and a real trade-off between reduced FWM and low bandwidth accompanied with low channel capacity. The author [12] has constructed a DWDM system with high conversion efficiency but difficulties in attaining phase-matching condition. A DWDM model has been proposed in Ref. [2] with a coherent modulation format and 3R system, which consumes about 90% transmission power at the receiver end. The author [16] has achieved the quality factor 30 dB, the gain 29.4 dB and the eye closure 0.9 dB in the presence of serious inter-symbol interference. In the work [4] an efficient wavelength-division multiplexing system has been suggested for the case of symbol rate 50 Gbaud, quadrature phase-shift keying and a 16-QAM modulation format. Unfortunately, this system has a reduced effeciency at above 100 Gbaud and 16-QAM, and the nonlinear compensation becomes difficult to perform. The model [9] for the 1000 km wavelength-division multiplexing system with non-RZ and RZ modulation formats reveals a relatively low quality of data transmission and a significantly low signal power. The work [13] has presented a DWDM design with 25 dB reduction of the FWM power, which has limited value in choosing modulation formats with optical filters. The author [14] has proposed a DWDM design characterized by low distortion, high quality factor and low BER. It is less affected by the fibre nonlinearity, although the computational method is time-consuming in performing iterative simulations. In Ref. [15], a hybrid DWDM with FWM suppression has been demonstrated. It has high enough gain and low input power, which have

been achieved using circular polarization of light. This system shows that the light-polarization state also affects the system efficiency.

In summary, the problems of taking into account the FWM effect in the DWDM systems using the quality-of-transmission predictions and performing self-parametric optimization based on the field requirements need their further investigations along the direction of ML approaches. The understanding of FWM-influencing parameters would enhance the quality-of-transmission parameter and reduce the uncertainty for reconfigured DWDM systems applied in the future communications with high data rates. Therefore, it would be useful to explore the ML-based supervised parametric prediction models. Here the understanding of the FWM-influencing parameters and the corresponding mitigating factors, as well as achieving of appreciable reduction in the FWM, should be obtained using training databases of well established data points.

Of course, the optical DWDM networks of future generations with good performance and secured data transfer need larger number of channels, lower channel spacing and higher input power. These constraints imposed upon the DWDM system introduce challenging nonlinear impairments exemplified well by the FWM effect, which degrades the system performance and reduces both the bandwidth utilization and the channel capacity. Furthermore, these DWDM limitations require a complex design of the system structure and make the systems difficult to implement. In the present work, we discuss a SRM algorithm based on ML, which avoids the complexity peculiar for the conventional parametric simulation approaches. Moreover, we design a self-optimized high-capacity DWDM system operating at 2.56 Tbps, which offers real parametric trade-offs and a reduced FWM. Finally, we quantify our SRM-DWDM model by comparing its results with the exact results.

3. Fundamentals of FWM

Let us consider an optical system where light propagates at three different wavelengths, with the corresponding frequencies being equal to F_i, F_j and F_k. Let an optical medium be characterized by a third-order susceptibility, which generates a fourth wave, of which frequency can be expressed as

$$F_{ijk} = F_i \pm F_j \pm F_k \ . \tag{1}$$

Here F_{ijk} is the inter-modulated signal, or a FWM, which degrades the system function. Using a Taylor expansion, one can represent the combined fifth-order effects of the FWM as follows:

$$B = B_0 + (\Omega - \Omega_0)\frac{d\beta}{d\Omega} + \frac{1}{2}(\Omega - \Omega_0)^2 \frac{d^2\beta}{d\Omega^2} + \frac{1}{6}(\Omega - \Omega_0)^3 \frac{d^3\beta}{d\Omega^3}$$
$$+ \frac{1}{d^4}(\Omega - \Omega_0)^4 \frac{d^4\beta}{d\Omega^4} + (\Omega - \Omega_0)^5 \frac{d^5\beta}{d\Omega^5} \tag{2}$$

where $d\beta/d\Omega = \tau$ is the propagation delay per optical length, $\Omega - \Omega_0$ the frequency deviation, $1/d^4$ the fourth-order dispersion factor, and B_0 the initial Taylor propagation factor. Since τ produces some phase delay, which does not influence the interference signal, it can be neglected. The phase-matching factor is defined as

$$\Delta\beta = 2\pi^2 \Delta f^2 \left(\begin{array}{l} \dfrac{\lambda^2}{2\Delta c} + \dfrac{2\pi\Delta f}{3}\dfrac{\lambda^2}{2\Delta c^2}(\lambda^2\Delta_1 + 2\lambda\Delta) + \dfrac{\pi^2}{3}\dfrac{\Delta f^2 \lambda^3}{(2\pi c)^3}(\lambda^3\Delta_2 + 6\lambda^2\Delta_1 + 6\lambda\Delta) \\ + \dfrac{2\pi^3}{15}\dfrac{\Delta f^3 \lambda^4}{(2\pi c)^4}(\lambda^4\Delta_3 + 12\lambda^4\Delta_2 + 36\lambda^4\Delta_1 + 24\lambda\Delta) \end{array} \right), \tag{3}$$

where λ stands for the wavelength, Δ_c the chromatic dispersion in fibre, Δf a function of channel

spacing, Δ a function of delay, and Δc a function of chromatic dispersion. Numerically, the FWM power can be easily expressed in terms of the input powers p_i, p_j and p_k at the frequencies F_i, F_j and F_k, and the effective length of optical fibre:

$$b_{FWM} = d_{ijk}^2 \, v^2 L_{eff}^2 \, p_i p_j p_k \eta_{ijk} e^{-2L}, \qquad (4)$$

where L denotes the length of fibre, d_{ijk} is either the degeneration factor (at the condition $i = k$) or the non-degenerative factor (at $i \neq k$), L_{eff} the effective length, v the nonlinear coefficient, and η_{ijk} the efficiency.

The nonlinear coefficient v reads as

$$v = \frac{2\pi\eta_2}{A_{eff}\lambda_0}, \qquad (5)$$

where η_2 is the refractive index of fibre core, A_{eff} the effective area of fibre, and λ_0 the operating wavelength (1550 nm in our case). The efficiency for the long-haul fibre due to FWM can be found from the relation

$$\eta_{ijk} = \frac{\alpha^2}{\alpha^2 + \Delta\eta B_{ijk}^2} \left(1 + \frac{4e^{-\alpha^2}\eta^2\left(\frac{\Delta B_{ijk}^2}{2}\right)}{\left(1 - e^{-\alpha^2}\right)^2} \right), \qquad (6)$$

where α denotes the attenuation factor, $\Delta\eta$ the variation of refractive index and B_{ijk} the phase-matching factors at the frequencies numbered as i, j and k. From the above relation, the product term with the exponential decay has no practical impact. So the simplified efficiency of the long-haul system is given by

$$\eta_{ijk} = \frac{\alpha^2}{\alpha^2 + \Delta\beta_{ijk}^2}, \qquad (7)$$

where $\Delta\beta_{ijk}$ denotes the phase-matching coefficient. As specified by the International Tele-communication Union for the DWDM systems with equal channel spacing, $\Delta\beta_{ijk}$ takes discrete values, which are multiples of 0.4 nm. Then the phase-matching coefficient can be written as

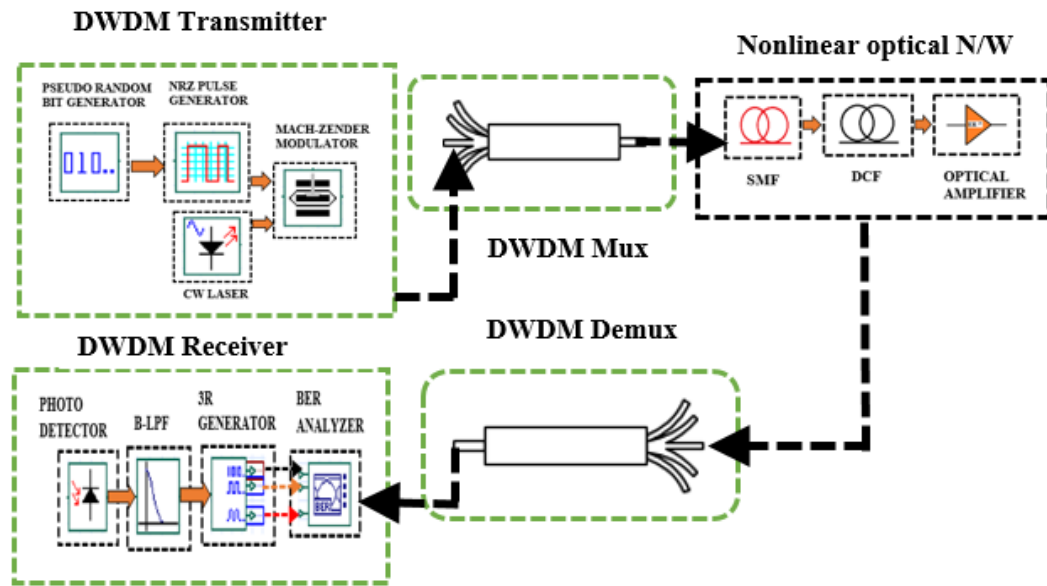$$\Delta\beta_n = n\left(\frac{d}{dv^2}\right)\Delta_c\Delta\lambda^2. \qquad (8)$$

Hence, the FWM efficiency depends upon the nonlinear refractive index η_2, the channel spacing $\Delta\lambda$, the dispersion coefficient δ and the effective area A_{eff} as follows:

$$\eta_{ijk} = \frac{\eta_2}{A_{eff}(\Delta\lambda)\delta}. \qquad (9)$$

Even the simplest analysis of the FWM testifies its importance and influence on the DWDM systems. This provides basic considerations of the need in mitigating the FWM for a conventional DWDM setup, provided that the DWDM functions such as channel spacing, optical gain, input power, data rate and other factors are known. Section 4 will explain the corresponding simulation setup, with detailed specification of all the procedures needed to perform the conventional simulation methodology.

4. Conventional simulation setup

Fig. 1 shows a schematic diagram of a DWDM system. At a transmitter end of this system, a pseudo-random bit generator acts as a data source and the rate 10 Gbps is used. The data of pseudo-random bit generator is converted into short electrical pulses through an electrical pulse generator, and a Mach−Zehnder modulator modulates these pulses. A DWDM multiplexer combines the input channels with the modulated optical signals and transmits them over a single-mode fibre having the dispersion 16.75 ps/nm/km and the attenuation 0.2 dB/km. The optical signal from the single-mode fibre is transmitted through an EDFA amplifier. In this Section, we suppose that the amplification process is performed and the amplified signal is accumulated with a greater amplified spontaneous-emission noise. The amplified signal passes through the dispersion-compensating fibre characterized by some attenuation and dispersion parameters. Here nonlinear properties of the optical fibre and the dispersion-compensating fibre are actuated.

Fig. 1. A basic scheme of optical DWDM network: SMF is a single-mode fibre and DCF a dispersion-compensated fibre.

At a receiver side, a DWDM demultiplexer splits the demultiplexed signals into individual channels. The output signal emergent from demultiplexer passes through a PIN photodetector where conversion of optical signal into electrical one is performed. Then a converted electrical signal passes through a low-pass Bessel filter. Finally, the spectrum of the output signal in the form of a so-called 'eye characteristics' is detected by a BER analyzer.

Note that a high-power signal travels a long distance in a long-haul fibre-optic DWDM system to reach a receiver and it is cumbered by the nonlinearities. The simulated optical DWDM network must be designed with taking into account various system-dependent parameters, including the data rate, the channel spacing, the modulation format, the input power and the parameters of optical amplifier. In the presence of FWM, estimation of such factors as the minimum bit error rate, the Q-factor, the OSNR, the output signal power and the noise power is also necessary for any consistent analysis of DWDM performance. Analysis of the duty cycle, the optical gain and the effective area of fibre core is required, too. Section 5 presents the SRM-DWDM model suggested by us and its methodology. The SRM is used for reducing the

conventional iterative runtime. Moreover, it provides many details necessary for calculating the optimized network structure.

5. SRM-DWDM system

To mitigate the FWM effect, we implement the SRM via obtaining datasets from different analyzers such as optical spectrum analyzer, BER analyzer and wavelength-division multiplexing analyzer. Monitoring of these datasets demands different configurations of DWDM to achieve a near-field accuracy. However, retrieving of data from different monitoring points is difficult. Therefore, a reliable ML model which employs a regression-modelling method has to be developed in order to identify the main FWM-influencing parameters (e.g., the channel spacing, the input power, the data rate, the modulation format and the core size of fibre). An ML-based SRM control unit (or SRM-CU) collects the required data from a long-term network monitoring. Fig. 2 suggests possible approaches applied for collecting real data from the DWDM network. They are used while developing the SRM.
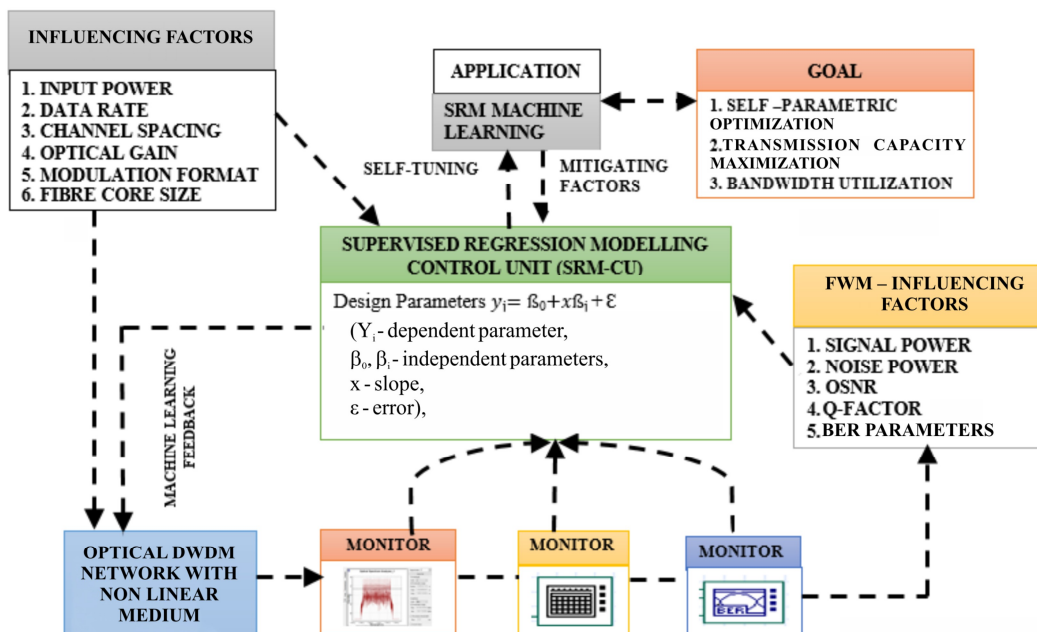

Fig. 2. A DWDM system with SRM suggested in the present work.

Fig. 2 illustrates functioning of our SRM-DWDM system (with a workflow used to retrieve the dataset and train the SRM), which performs a self-parametric optimization and mitigates the FWM. This setup analyzes the FWM-influencing parameters and the FWM-mitigating factors such as the maximal Q-factor (or simply Max Q-factor), the minimal BER (Min BER), the noise power and the OSNR from the long-term data-monitoring process. The appropriate aim is to develop the SRM and perform the self-parametric optimization. The SRM is built for different system functions and different factors that mitigate the FWM. Each factor is evaluated by a strength of correlation and a corresponding R-value.

Our SRM-DWDM system is designed basing on real-time constraints. This design is tuned via the FWM-influencing parameters: the input power, the data rate, the channel spacing, the modulation format and the optical gain. Then we analyze their influence on a high-capacity DWDM system. In this analysis, the FWM and its relationships with various influencing

parameters are addressed. Their influence on bandwidth utilization and transmission capacity is modelled through the SRM-DWDM approach.

The SRM-DWDM system is studied using various conventional parametric simulation methods at different system functions and factors mitigating the FWM. The results are monitored with the wavelength-division multiplexing analyzer, the optical spectrum analyzer and the BER analyzer. The datasets are retrieved from the long-term network monitoring and fed into the SRM-CU. The SRM-CU develops a knowledge database to perform the self-parametric optimization and collect much enough data for training our SRM-DWDM system. Finally, the SRM-CU is trained on different datasets from different configurations of the high-capacity DWDM system. The R-value obtained through the SRM shows the correlation level between the system functions and the mitigating factors. The R-values are also calculated in the SRM-CU.

Let us denote different values of the system variables (e.g., the input power, the channel spacing, the optical gain, the duty cycle and the bit rate) as x. In SRM-CU, the mitigating factors that influence the nonlinearities (e.g., the output signal power, the noise power, the OSNR, the eye height and the Max Q-factor) are considered as y's, with ε being the error values. We collect n such data points. Hence, our data points are $\left\{\left(x_j, y_j\right), \text{where } j = 1, 2, \ldots\ldots n\right\}$. The supervised regression equation for the data is given by

$$y_j = \beta_0 + x\beta_j + \varepsilon \ , \tag{10}$$

where β_0's are intersects and β_j the slopes. By substituting the values obtained from simulations based upon Eq. (10), one can derive the SRM for different factors. Various iterative simulations are carried out by varying each of the system functions while keeping the others constant. The SRM-CU gets different values obtained from these factors, performs averaging and develops the SRM equation. The R-values achieved in this procedure show the correlations between different factors and a given system function. The levels of these correlations, which are distinguished by us, are shown in Table 1.

Table 1. R-values and their distinguished correlation levels.

#	R-value	Correlation level
1	$1 \geq R \geq 0.8$	High
2	$0.7 \geq R \geq 0.5$	Moderate
3	$0.4 \geq R \geq 0.3$	Low
4	$0.2 \geq R \geq 0.1$	Very low
5	Negative R value	No

The above calculations have been performed for the training dataset received from the SRM-CU. For example, one of the equations obtained for the 1.28 Tbps DWDM network configuration is as follows:

$$\text{output signal power} = [-0.4729] \times [\text{bit rate}] + [10.2464],$$

with the R-value being equal to 0.9362. From the above study, the correlation between the output signal power and the input power can be highlighted by the R-value. The figure 0.9362 demonstrates that the correlation between the input power and the output signal power is strong. On the other hand, we have

$$\text{OSNR} = [-0.2555] \times [\text{bit rate}] + [51.4391],$$

with the R-value = 0.4269. This proves that there is a low correlation between the input power and the OSNR.

In Section 6, we will compare the estimated parameters of our SRM-DWDM model with their true values, in particular for the Q-factor, the noise power, the OSNR, the signal power and the eye height. Then the accuracy of the SRM-DWDM model can be estimated by a difference between the estimated and true values, which is treated as an error.

6. Testing of SRM-DWDM system and parametric observations

The self-parametric optimization is performed through a trained knowledge database acquired from the SRM-CU block mentioned in Fig. 2. Prioritization of the nonlinear effects occurring in the DWDM system enhances its performance and reduces its complexity. Our model is developed basing on the SRM, which provides the correlation levels for the relationships among the FWM-mitigating factors and the system functions (e.g., the channel spacing, the input power, the bit rate, the modulation format, the core size of fibre and the optical gain). Notice that high-capacity DWDM systems with higher-order modulations are more sensitive to the FWM. Our model can also be used for the higher-order modulated DWDM systems, thus providing basic understanding of the FWM-influencing factors. Here the correlation level of a given mitigating factor shows how much this factor can influence a given system function. This helps in building dynamically a self-optimized system using the SRM-DWDM approach. The corresponding equations developed from the SRM-DWDM are used to find the correlations of different factors with the system functions.

We have developed the supervised regression models for the particular cases of 1.28 Tbps and 2.56 Tbps data rates. Since the efficient high-capacity DWDM systems must involve a high input power, a large number of channels, low channel spacing and a low-distortion modulation format, we have modelled our DWDM as being operated at the data rate 10 Gbps, the narrow channel spacing (50 GHz), the input power 10 dBm, the fibre-core size 80 μm and the RZ modulation format with the duty cycle 0.25%. To perform the SRM, every of these parameters is varied while keeping the other parameters invariable. The conventional iterative results, i.e. the true results, are gathered with the simulations performed via OptiSystem. These true iterative results are considered as a trained database. They we feed the SRM-CU with these values to train it. The number n of those iterations is large enough.

Table 2. Conventional iteration results obtained for the 1.28 Tbps system at different bit rates.

Bit rate	Signal power, dBm	Noise power, dBm	OSNR, dB	Max Q-factor	Min BER	Eye height
2.5	9.339	−42.314	51.654	29.743	2.27E−195	0.00271
5.0	7.864	−42.218	50.082	64.760	0	0.00207
7.5	5.910	−41.211	47.121	71.760	0	0.000756
10.0	6.050	−44.462	50.512	77.761	0	0.000924

The regression-model equations have been built for our SRM-DWDM system. So, when the input power is 10 dBm in the 1.28 Tbps system, we obtain

$$\text{output signal power} = [0.999] \times [\text{input power}] + [16.271],$$

with the R-value 1.000. From Table 2, the bit rate and the output signal power are correlated. Issuing from the R-value, the relationship between the input power and the output signal power is significant. The 'true' value 26.231 dBm and the estimated value 26.261 dBm are obtained for this mitigating factor, with a low marginal error of 0.0298. Similarly, for the other FWM-mitigating

factor in the same DWDM configuration and the input power 10 dBm we have

$$\text{eye height} = [0.0011] \times [\text{input power}] + [0.0064],$$

with the R-value 0.0865. It is seen from Table 2 that the bit rate and the other FWM-mitigating factors such as the output signal power and the eye height are also correlated. There is very weak relationship between the input power and the eye height, since the R-value is very low. Furthermore, wide marginal errors are obtained for the true (0.0263) and estimated (0.0174) values of the eye-height factor. In other words, the true and estimated values of the eye-height factor reveal high marginal deviations. The similar results can be observed with the probability plots for the eye-height characteristics. Obviously, much larger numbers of trained datasets are needed to achieve higher accuracy and lower marginal errors for the eye-height factor.

In a quite similar manner, the regression-model equations have been developed for the other combinations of the influencing parameters to understand their effects on the FWM. This is necessary for structuring well our high-capacity SRM-DWDM so that it met the global optimization requirements.
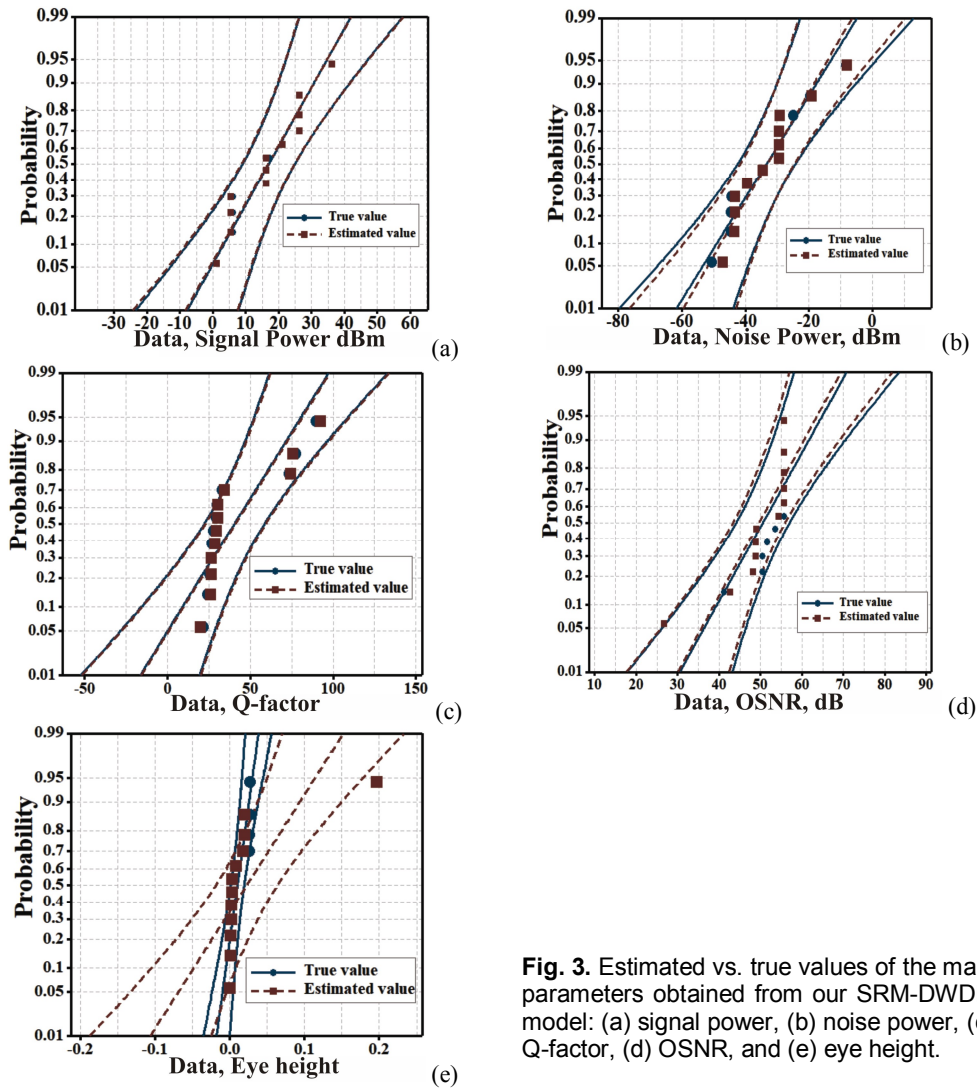
Table 3. Mean, standard deviation, P-value and Anderson−Darling factor obtained for the parameters that influence the FWM nonlinearity, using our SRM-DWDM system.

Parameter	Mean	Standard deviation	Anderson−Darling factor	P-value
Signal power, dBm	17.11	10.68	0.367	0.371
	16.88	10.83	0.400	0.306
Noise power, dBm	−33.26	12.22	0.298	0.63
	−33.02	11.43	0.477	0.193
Q-factor	40.6	24.43	1.778	< 0.005
	41.31	24.49	1.677	< 0.005
OSNR, dB	50.71	8.653	1.700	< 0.005
	49.78	8.452	1.216	< 0.005
Eye height	0.0104	0.0121	1.605	< 0.005
	0.0229	0.0554	2.909	< 0.005

The SRM equations applied in different ranges of the bit rate and the appropriate results predicted for different mitigating factors in the 1.28 and 2.56 Tbps DWDM configurations are qualitatively the same. The SRM-based estimated value in this case has also been verified after simulating the same parameter, which is given as an input to the regression equation. Following from the SRM-CU knowledge database, we conclude that the Q-factor, the signal power, the noise power and the OSNR manifest very low marginal error differences between the estimated and true values. On the contrary, the estimated values of the eye height show more deviations when compared to the true values observed from the conventional iterations. To reduce this error difference, a more trained dataset for the eye height must have been analyzed. In general, validation process has yielded in very similar sets of results in the both calculations, which demonstrates a remarkable accuracy of global optimization and offers real trade-offs among user-based requirements.

The error difference parameters derived as explained above can be fitted well by the normal probability distribution. Table 3 presents the mean and the standard deviation for both the true and

estimated values in our SRM-DWDM system, as obtained for the cases of 1.28 and 2.56 Tbps bit-rate fibre-optic systems.

Fig. 3. Estimated vs. true values of the main parameters obtained from our SRM-DWDM model: (a) signal power, (b) noise power, (c) Q-factor, (d) OSNR, and (e) eye height.

Fig. 3 shows the normal probability plots for the FWM-mitigating factors (the signal power, the noise power, the Q-factor, the OSNR and the eye height), which have been obtained from the long-term network monitoring and the SRM-DWDM modelling. It is evident that, except for the eye height, all the remaining factors follow closely the ideal normal distribution. The Anderson−Darling method receives the dataset from the SRM-CU, checks the flow of estimated values following the true values and analyzes the distribution. The estimated values of the signal power, the noise power, the Q-factor and the OSNR in the plots fall on straight lines as functions of the true values. Fig. 3 testifies that the SRM-DWDM-based distributions are close to the actual underlying distribution. Except for the eye height, the distribution plots obtained for all the other parameters reveal no enough evidence for extra deviations from the normal distribution. Unlike all the other parameters, the deviations for the eye-height characteristic expressed in terms of the mean and standard deviation are severe and do not follow the normal distribution (see Table 3). Further investigations must be carried out to understand better the eye-height characteristic and reduce the error margins.

6.1. Effects of bit rate

Fig. 4 displays the spectral data obtained for the 256-channel network operating at different bit rates, using our SRM-DWDM system. In this setup, the bit rate varies from 2.5 to 10 Gbps and the remaining system parameters are kept constant.
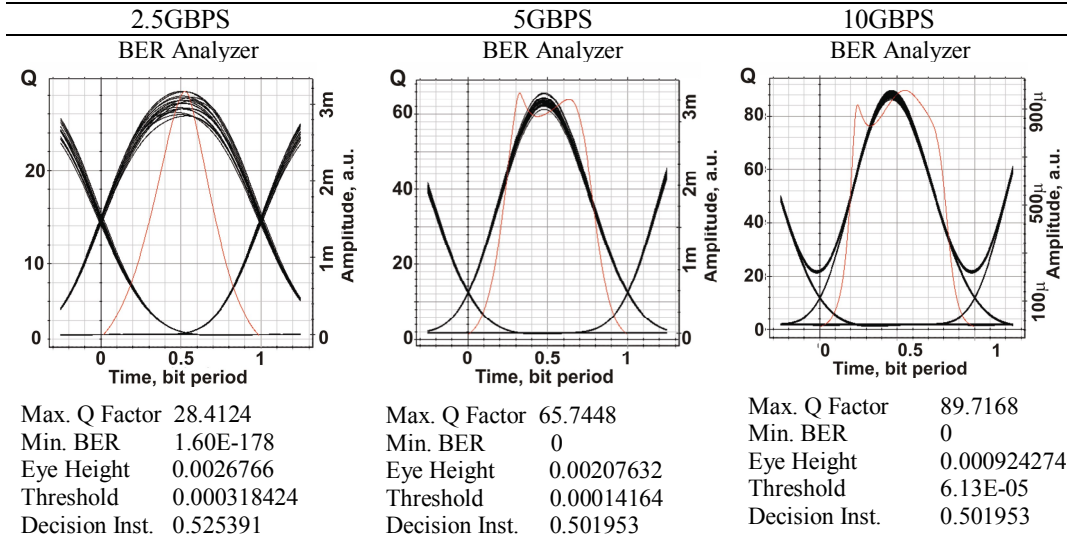
2.5GBPS	5GBPS	10GBPS
BER Analyzer	BER Analyzer	BER Analyzer

Max. Q Factor	28.4124	Max. Q Factor	65.7448	Max. Q Factor	89.7168
Min. BER	1.60E-178	Min. BER	0	Min. BER	0
Eye Height	0.0026766	Eye Height	0.00207632	Eye Height	0.000924274
Threshold	0.000318424	Threshold	0.00014164	Threshold	6.13E-05
Decision Inst.	0.525391	Decision Inst.	0.501953	Decision Inst.	0.501953

Fig. 4. Spectral analysis data obtained for 2.56 Tbps DWDM system at different bit rates.

One can see from this simulation results that the output signal power, the Q-factor, the BER and the eye diagram have a direct impact on the FWM nonlinearity, which degrades the performance of optical DWDM systems. Increasing the data rate stipulates higher dispersion which introduces pulse broadening and creates more noise interference in the DWDM system. As seen from the eye characteristic shown in Fig. 4, the output spectral characteristic at 10 Gbps shows low eye height (~ 0.0009) and high enough pulse broadening in the output signal. Such factors as the output signal power, the noise power and the OSNR also have their impact due to occurrence of dispersion in the DWDM system, which affects the Q-factor. Simulations for the SRM-based data obtained for the 128- and 256-channel capacities testify that the input power is highly correlated with the output signal power, the eye height and the Max Q-factor, which is seen from the corresponding R-values.

6.2. Effects of channel spacing

In this section we study SRM-DWDM results obtained at the channel spacings varying from 25 to 100 GHz in case of the 128- and 256-channel configurations. The channel spacing is a key simulated parameter, which is inversely related to the system functions that mitigate the FWM in a fibre-optic DWDM system. After analyzing the datasets from different configurations, one can conclude that the system with 128 channels utilizes the channel spacing very well if compared to the case of 256 channels. It is seen from Fig. 5 that the system with narrow channel spacing (25 GHz) has a greater noise interference, which imposes a distorted eye height and a poor Q-factor. The system with 100 GHz channel spacing shows a very good eye height, a high Q-factor, a low BER and a very efficient eye characteristic. The OSNR and the Q-factor are closely correlated and have a positive impact, irrespective of the channel spacing. The channel spacing is a real trade-off factor, which needs to be optimized basing on user requirements (e.g., large number of

channels and extremely good bandwidth utilization). Finally, our SRM-DWDM technique reveals that increasing channel spacing lowers the FWM and provides a sufficient Q-factor with a very good eye height.
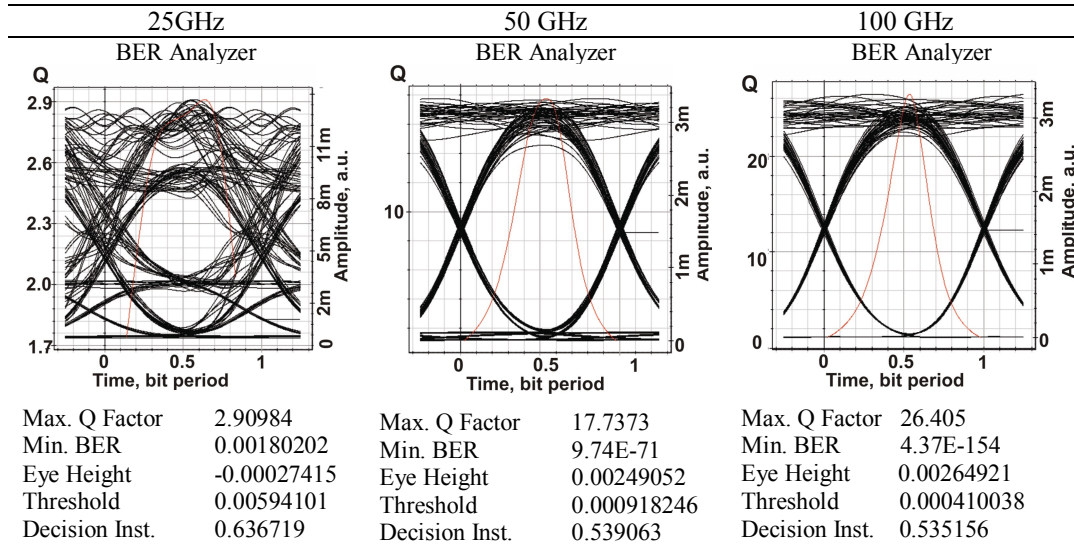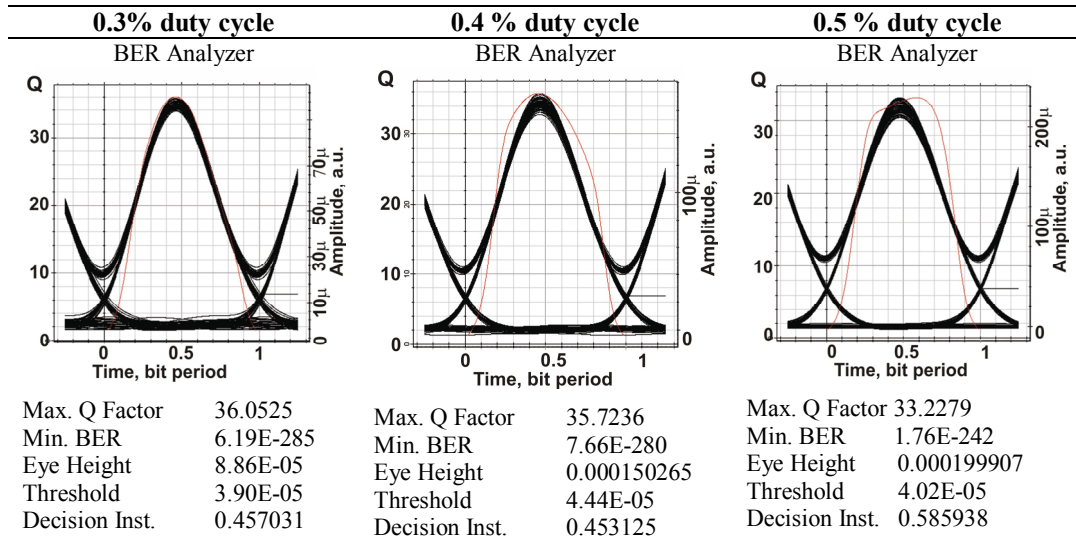

	25GHz		50 GHz		100 GHz
Max. Q Factor	2.90984	Max. Q Factor	17.7373	Max. Q Factor	26.405
Min. BER	0.00180202	Min. BER	9.74E-71	Min. BER	4.37E-154
Eye Height	-0.00027415	Eye Height	0.00249052	Eye Height	0.00264921
Threshold	0.00594101	Threshold	0.000918246	Threshold	0.000410038
Decision Inst.	0.636719	Decision Inst.	0.539063	Decision Inst.	0.535156

Fig. 5. Spectral analysis data obtained for a 1.28 Tbps DWDM system at different channel spacings.

6.3. Effects of RZ modulation at different duty cycles

Fig. 6 displays the spectral characteristics obtained by our SRM-DWDM system at the RZ modulation and different duty cycles (from 0.25 to 0.50). They all refer to the 256-channel capacity. In long-haul DWDM data transmission, the RZ and NRZ modulation formats are widely used. The RZ format is a key method used up to 2.56 Tbps, since it is characterized by higher OSNR and peak power and lower BER than those typical for the other modulation formats. It is also known that this format provides good immunity against the nonlinear effects in fibre-optic systems and so is capable of mitigating the FWM effect.

Our SRM-based modelling has provided the R-values and the corresponding correlation levels for the Q-factor, the BER, the output signal power, the OSNR and the noise power. The noise power reveals a moderate correlation, with the R-value equal to ~ 0.678. The Q-factor and the eye height show higher correlations at the RZ modulation and varying duty cycle, which proves its high immunity against the FWM nonlinearities. As a consequence, the results of our SRM-DWDM technique testify the fact of sufficient data transmission level, with high Q-factor, low BER and good eye height.
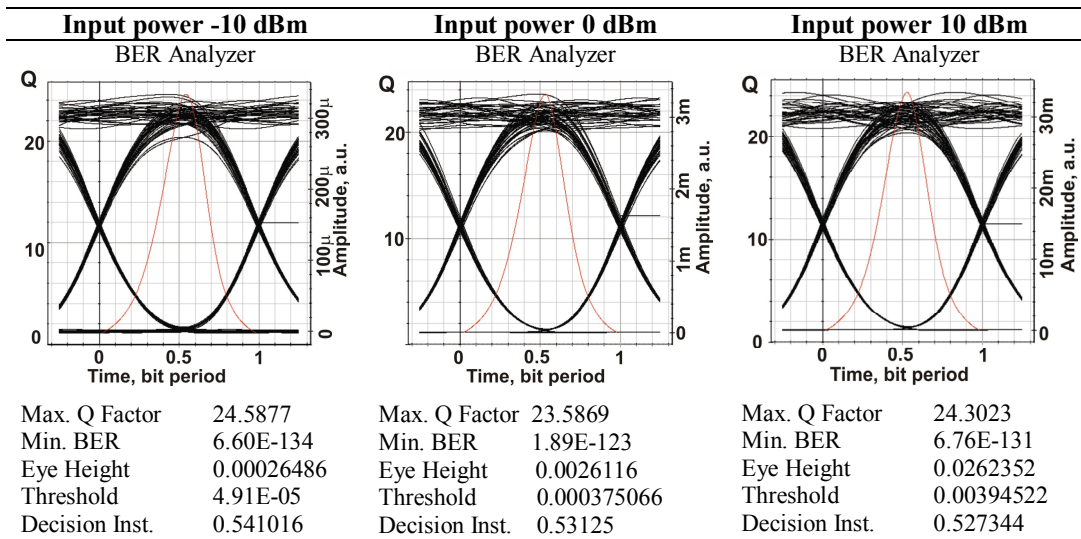
One can see from Fig. 6 that the RZ modulation format with the duty cycle 0.3 has a good Q-factor (~ 36.05), the eye height 8.86×10^{-5} and a narrow output pulse. The other duty cycles reveal the occurrence of broadened output-pulse characteristics in the presence of nonlinearities. These results are also directly reflected in the other FWM-mitigating factors such as Min BER, the OSNR, the Q-factor, the output signal power and the noise power. This drops down the system performance. One can conclude from the SRM analysis that the system with the RZ modulation and variable duty cycle behaves better than the other compensation schemes. We observe marginal correlations for the eye height, the output signal power and the noise power, which influence the Q-factor and the parameter Min BER identically.

0.3% duty cycle	0.4 % duty cycle	0.5 % duty cycle
BER Analyzer	BER Analyzer	BER Analyzer

Max. Q Factor	36.0525	Max. Q Factor	35.7236	Max. Q Factor 33.2279
Min. BER	6.19E-285	Min. BER	7.66E-280	Min. BER 1.76E-242
Eye Height	8.86E-05	Eye Height	0.000150265	Eye Height 0.000199907
Threshold	3.90E-05	Threshold	4.44E-05	Threshold 4.02E-05
Decision Inst.	0.457031	Decision Inst.	0.453125	Decision Inst. 0.585938

Fig. 6. Spectral analysis data obtained for a 2.56 Tbps DWDM system at RZ modulation format and different duty cycles.

6.4. Effects of input power

The input power is the most investigated and highly correlated system parameter that directly affects all the factors influencing the FWM nonlinearities in fibre-optic DWDM systems. Fig. 7 shows the spectral characteristics obtained with our SRM-DWDM system at different input powers (from 10 to −10 dBm). The resultant spectral characteristics confirm that variations in the input power affect directly the FWM nonlinearities in the DWDM system. This phenomenon is proven by the correlation analysis, which shows that the output signal power, the noise power, the Q-factor, the BER and the eye diagram are highly correlated with the input power. In other words, any variations in this power would influence hard all of these parameters and make high impact on the nonlinearity. It would be useful to find the optimized input power to transmit data efficiently over long distances.

Input power -10 dBm	Input power 0 dBm	Input power 10 dBm
BER Analyzer	BER Analyzer	BER Analyzer

Max. Q Factor	24.5877	Max. Q Factor	23.5869	Max. Q Factor	24.3023
Min. BER	6.60E-134	Min. BER	1.89E-123	Min. BER	6.76E-131
Eye Height	0.00026486	Eye Height	0.0026116	Eye Height	0.0262352
Threshold	4.91E-05	Threshold	0.000375066	Threshold	0.00394522
Decision Inst.	0.541016	Decision Inst.	0.53125	Decision Inst.	0.527344

Fig. 7. Spectral analysis data obtained for a 1.28 Tbps DWDM system at different input powers.

In general, the optimal input power varies depending on the transmission distance and the other system parameters. It is evident from Fig. 7 that, for a 128-channel system, the OSNR decreases with decreasing input power. One has the BER 6.6×10^{-134}, the eye height ~ 0.0003 and the maximum quality factor ~ 24.6, which are larger than those obtained for a 256-channel system. The input power is linearly related to the output signal power, the noise power, the Q-factor and the eye height. The SRM-DWDM results associated with high R-values and good correlations among the output signal power, the noise power, the Q-factor and the eye height prove that any deviations in the input power influence notably the FWM, which can degrade the system parameters.

6.5. Effects of core size of optical fibre

The effective area of the fibre-core size influences the FWM. Namely, increasing core size reduces proportionally the effective core area and so results in diminishing the FWM. In our study, the effective core radius varies from 80 to 160 μm. The appropriate simulation results are presented in Fig. 8. One can see that the effect of FWM is essential for large numbers of channels and high data rates, which lowers the system performance. This is clearly visible from our SRM-based study, which demonstrates that increasing effective core radius reduces the FWM.
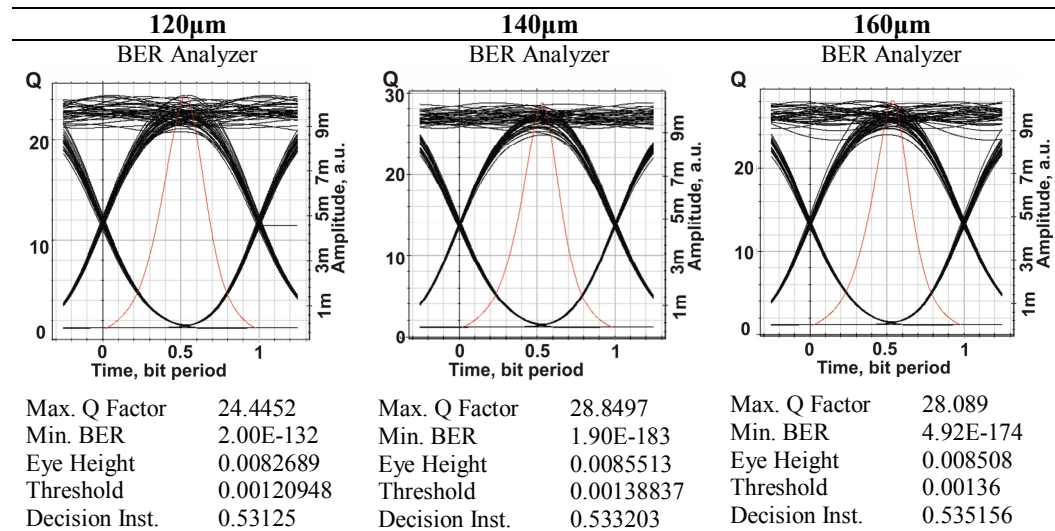

	120μm		140μm		160μm
Max. Q Factor	24.4452	Max. Q Factor	28.8497	Max. Q Factor	28.089
Min. BER	2.00E-132	Min. BER	1.90E-183	Min. BER	4.92E-174
Eye Height	0.0082689	Eye Height	0.0085513	Eye Height	0.008508
Threshold	0.00120948	Threshold	0.00138837	Threshold	0.00136
Decision Inst.	0.53125	Decision Inst.	0.533203	Decision Inst.	0.535156

Fig. 8. Spectral analysis data obtained for a 2.56 Tbps DWDM system at different core sizes of optical fibre.

Our SRM-based results derived from the statistical data obtained by simulating the DWDM system at different core sizes show that a variable input power is directly related to the noise power. Then the increasing noise power influences the remaining parameters so that the complete system performance degrades.

6.6. Effects of optical gain

Our last simulations refer to the SRM-DWDM data obtained at varying gain of optical amplifier, under condition that the rest of the parameters are constant. The SRM analysis reveals high enough R-values for the output signal power, the noise power, the Q-factor and the eye diagram. Again, we have good enough spectral characteristics and mitigation of the FWM effect. In other words, such nonlinearity-influencing factors as the output signal power, the noise power, the Q-factor and the eye diagram are highly subjected to changes in the optical-amplifier gain.

The SRM-DWDM data at high optical gains implies high output power, along with high FWM power. The simulation results also reveal a better performance of the 256-channel system, which has a small improvement in the BER (5.03×10^{-163}), the eye height ~ 0.0267 and the Q-factor 27.172, whereas the rest of the outputs remain similar, except for the OSNR and the output signal power which become slightly improved. Our SRM-DWDM analysis yields in high R-values, which shows strong correlations of all the parameters such as the output signal power, the noise power, the Q-factor and the eye characteristic.
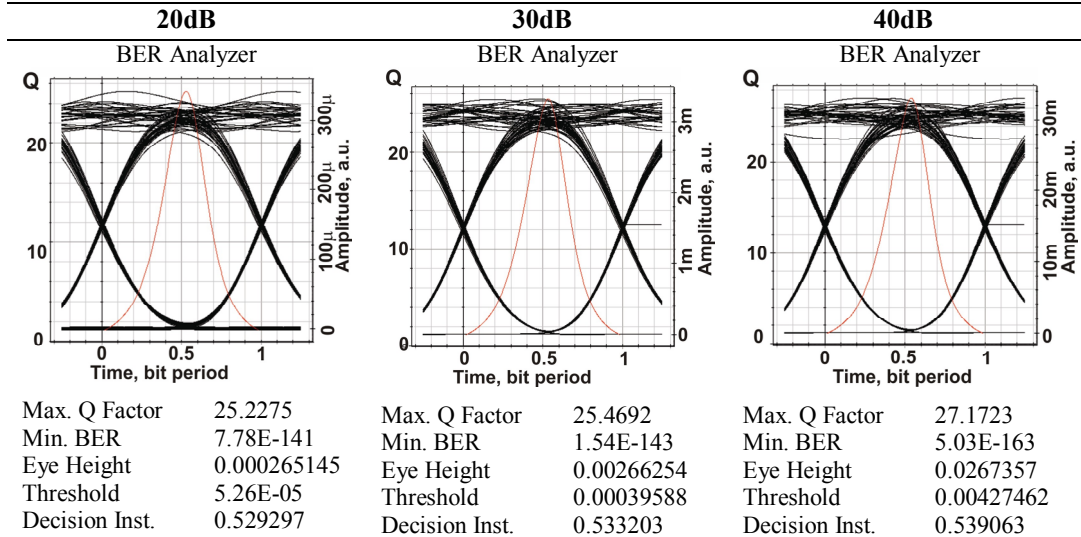
20dB	30dB	40dB
BER Analyzer	BER Analyzer	BER Analyzer

	20dB		30dB		40dB
Max. Q Factor	25.2275	Max. Q Factor	25.4692	Max. Q Factor	27.1723
Min. BER	7.78E-141	Min. BER	1.54E-143	Min. BER	5.03E-163
Eye Height	0.000265145	Eye Height	0.00266254	Eye Height	0.0267357
Threshold	5.26E-05	Threshold	0.00039588	Threshold	0.00427462
Decision Inst.	0.529297	Decision Inst.	0.533203	Decision Inst.	0.539063

Fig. 9. Spectral analysis data obtained for a 2.56 Tbps DWDM system at different optical gains.

7. Conclusions

In the present work, the self-parametric optimization of the high-capacity DWDM system is performed through the ML-based SRM scheme under a complicated condition of FWM effect present. According to our approach, the SRM-CU analyzes the dataset from the trained knowledgebase and provides the R-value. Then the calculations are performed for different combinations of the FWM-influencing parameters. We achieve a high enough accuracy to meet the requirements for trade-off among such factors as the maximal Q-factor, the minimal BER, the output power and the OSNR, in order to mitigate the FWM and cross-talks in the DWDM system. In our SRM-DWDM method, the estimated values of the eye height deviate significantly from the true values. Further investigations are needed to understand the eye-height characteristic and reduce the corresponding error margins. In general, our SRM-DWDM approach makes the DWDM design more reliable, easy and efficient. As a consequence, this can ensure higher quality of data transmission over longer distances.

Hence, we declare a consistent design of high-capacity DWDM systems and solving a complex problem of FWM nonlinearity, using the SRM-based analytical models. It also enables deriving some input−output relations among the system functions and its desired output parameters. The SRM can ensure extensive studies of the parameters and the factors that mitigate the FWM effect. The SRM technique applied to high-capacity DWDM systems enables one to understand and classify the data automatically and associate a streamline analysis for meeting complex system-design requirements, thereby reducing the system complexity and the computational runtime. A clear comparison of the estimated and true (iterative) results for any

DWDM system provides a firm ground for both evaluation and verification of the SRM-DWDM approach, which is based upon calculations of the accuracy levels through the marginal errors.

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Анотація. *Нещодавня глобальна криза, пов'язана з COVID-19, спонукала мільйони людей працювати вдома, що спричинило різке збільшення загального мережевого трафіку, вимог до швидкості передачі даних та кінцевих можливостей мережі. Це також спричинило більше шумів, перехресних завад і небажаних нелінійностей оптичного волокна, особливо ефекту чотирихвильового змішування (ЧХЗ), який погіршує роботу систем мультиплексування зі щільним поділом довжини хвилі (МЩПХ). Наявність ЧХЗ у системах МЩПХ спонукає зростаючу складність та інерційність мереж і знижує їхню спектральну ефективність. У свою чергу, це погіршує ефективне використання оптичної смуги*

пропускання. Щоби пом'якшити зазначені проблеми, ми пропонуємо регресійне моделювання з учителем (РМУ). Відповідний підхід РМУ-МЦПХ здійснює автоматизовану оптимізацію систем МЦПХ за допомогою методів машинного навчання і знаходить реальні компроміси серед різних факторів, що впливають на ЧХЗ. Наша модель понижує складність системи та час обчислень, що приводить до точного та надійного прогнозування значень параметрів. Ми також оцінили ефективність методики РМУ-МЦПХ, порівнюючи її дані з результатами, одержаними ітераційними методами для різних параметрів (наприклад, для відношення вихідного сигналу до шуму, Q-коефіцієнта, потужності сигналу та потужності шуму). Нарешті, у роботі описано процедури, необхідні для глобальної оптимізації систем МЦПХ.

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