Inverse design of programmable optical frequency comb using deep learning

IOP Publishing Journal of Optics
J. Opt. **24** (2022) 085702 (7pp) https://doi.org/10.1088/2040-8986/ac7c79

Inverse design of programmable optical frequency comb using deep learning

Yunjie Ma, Peili Li* and Weihua Shi

College of Electronic and Optical Engineering, Nanjing University of Posts and Telecommunications, Nanjing 210023, People's Republic of China

E-mail: lipl@njupt.edu.cn

Received 1 April 2022, revised 23 June 2022
Accepted for publication 28 June 2022
Published 14 July 2022

Abstract

Optical frequency comb (OFC) has important applications in measurement, communication, military and other fields. Usually, OFC needs to be designed according to different applications. However, the existing methods to design the operating parameters of the OFC generators are time-consuming, inefficient, and difficult to achieve optimal results. In this paper, a novel method of inversely designing OFC using deep learning, which is real-time and can improve the performance of the generated OFC, is proposed and applied to an OFC generator based on a single dual-drive Mach–Zehnder modulator. In this method, according to the required target OFC, the trained neural network can be used to inversely design the corresponding parameters. Using this inverse design method, the generated OFC not only is highly consistent with the target OFC, but also has the programmability of comb-line number, comb-line power, side mode suppression ratio, and comb spacing. Moreover, the proposed method can be utilized for more complicated OFC generator, and is an inspiration for efficient design of OFC.

Supplementary material for this article is available online

Keywords: optical frequency comb, deep learning, inverse design, optical communications

(Some figures may appear in colour only in the online journal)

1. Introduction

Optical frequency comb (OFC), whose spectrum consists of a series of discrete, equally spaced frequency lines, has generated strong impetus and far-reaching influence in optical precision measurement, optical communication, optical sensing, military, and other fields [1–5]. The generation technologies of OFC mainly include mode-locked lasers [6, 7], nonlinear effects [8, 9], micro-ring resonators [10, 11], photoelectric oscillators [12, 13] and electro-optic modulators [14, 15]. Among them, OFC generation technology based on electro-optic modulators has been widely studied due to its advantages of simple structure and flexible comb spacing. However, even for a very simple OFC generator, the whole system is nonlinear and the power distribution of the comb is not uniform. It is difficult to obtain the exact correspondence between the operating parameters and OFC, which makes it difficult to obtain the OFC with flat power.

Among the study of OFC based on electro-optic modulators [14–18], the control variate method is the main approach, which fixes some parameters from the beginning and change one variable at a time. However, this conventional method requires researchs' extensive experience to determine the key parameters. The fixed parameters limit the solution domain and make it difficult to obtain a global optimal result with extreme inefficiency. Furthermore, in the OFC generation technology based on multiple radio frequency (RF) signals driving a single modulator [19] or cascaded modulators [20, 21], it is more difficult for the control variate method to obtain an optimal solution with the increase of parameters number that can be designed. In addition, the existing

* Author to whom any correspondence should be addressed.

OFC generation technologies still have the problem of lack of programmability, and the programmability of comb-line number is not flexible enough.

In recent years, optimization algorithms have been used in OFC generation technology to improve design efficiency. The differential evolution algorithm is applied to the OFC generator based on cascaded Mach–Zehnder modulators (MZMs) [22] and dual parallel MZMs [23] to optimize the amplitudes of the driving voltages and bias voltages of the two MZMs. The OFC with 7 comb lines and good flatness (<2 dB) is obtained. Pinto *et al* also use a differential evolution algorithm to optimize the amplitude and phase of multiple RF signals to modulate the laser and obtain 7 comb lines with a flatness of about 2 dB in the experiment [24]. Although the optimization algorithm can search a large variable space more easily and get a global optimal solution, it is disadvantages are obvious: the complexity of the algorithm will rise sharply with the increase of parameters number, and it becomes easy to fall into local optimal solution. In addition, for different target OFC, optimization algorithms require lots of iterations every time, which consuming plenty of time and computing resource. Thus, it is impossible to provide design parameters in real-time.

To further improve the efficiency of parameter design of OFC generator, a novel inverse design method using deep learning is proposed. With its unique feature learning, strong modeling ability and generalization ability, deep learning not only is widely used in image, speech, intelligent driving, but also can effectively solve some scientific problems that traditionally require researchers' insight on complex mechanisms. The inverse design method for OFC using deep learning overcomes the poor efficiency of the control variate method, and frees researchers from complex parameter setting. Compared with the optimization algorithms-based OFC study, deep learning-based inverse design method can deal with larger data dimensions easily and output optimal results in real time. It should be noted that, the training of the neural network may consume a certain amount of time, but it is an one-time cost, which is a significant feature. The proposed method can be extended to the optimization of more complex systems and has incomparable advantages in OFC generation technology.

This article is organized as follows. In section 2, the OFC inverse design method based on deep learning is introduced by taking a dual-drive Mach–Zehnder modulator (DDMZM) driven by RF signal as an example. The architecture of neural network and training method are presented in detail in section 3. In section 4, the programmability of comb-line number, comb power, side mode suppression ratio (SMSR), and comb spacing of the generated OFC are studied. Section 5 summarizes the contributions of this inverse design method for OFC.

2. Principles and methods

The schematic of OFC generator based on single-frequency signal and DDMZM is shown in figure 1(a). Sinusoidal signal of frequency f_c is applied to the upper and lower arms of DDMZM after amplification by an electric amplifier and splitter, respectively. The attenuator is used to adjust the amplitude difference of the upper and lower arm signals, and the phase shifter is used to tune the phase difference. The RF signal applied to two arms can be expressed as $V_{\text{upper}}(t) = V_1 \sin(2\pi f_c t)$, $V_{\text{lower}}(t) = V_2 \sin(2\pi f_c t)$, respectively, where V_1 and V_2 are the amplitude of the RF signal of the upper and lower arm.

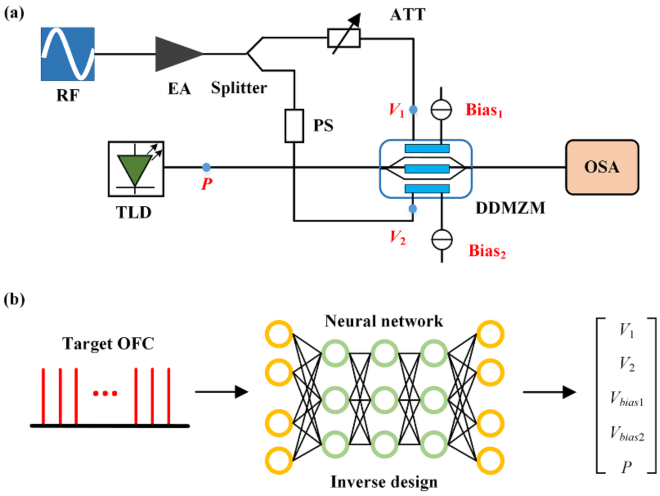

Figure 1. Schematic diagram of inverse design of programmable OFC based on deep learning: (a) OFC generator based on single frequency signal and DDMZM; (b) inverse design of working parameters based on deep learning.

A continuous laser of the center frequency f_0 is injected into DDMZM, in which intensity modulation and phase modulation occur. The output of DDMZM can be expressed as:

$$E_{\text{out}}(t) = \frac{E_{\text{in}}(t)}{2} \sum_{n=-\infty}^{\infty} \left[J_n(K_1) e^{j(2\pi n f_c t + \theta_1)} + J_n(K_2) e^{j(2\pi n f_c t + \theta_2)} \right] \quad (1)$$

where $E_{\text{in}}(t)$ is the continuous laser output, $J_n(\cdot)$ denotes the nth-order Bessel function of the first kind, $K_1 = \pi V_1 / V_\pi$ and $K_2 = \pi V_2 / V_\pi$ are the modulation index of the upper and lower arms respectively, and $\theta_1 = \pi V_{\text{bias1}} / V_\pi$ and $\theta_2 = \pi V_{\text{bias2}} / V_\pi$ are the phase shifts introduced by the upper arm bias voltage V_{bias1} and the lower arm bias voltage V_{bias2} respectively. The OFC of center frequency f_0 and frequency interval f_c can be obtained.

The number of comb lines can be adjusted by changing the modulation voltages of DDMZM arms (V_1, V_2). The comb spacing of OFC is equal to the frequency (f_c) of the RF signal. The flatness and comb power are related to the bias voltages (V_{bias1}, V_{bias2}) and the optical power (P) of the laser [25]. Therefore, by properly setting operating parameters, OFC with programmable comb-line number, comb sapcing and high power flatness can be generated.

Figure 1(b) shows the schematic diagram of inverse design of working parameters based on deep learning. The neural network consists of an input layer, some hidden layers and an output layer, whose detail can be seen in section 3. The comb-line number, comb power, comb spacing, and SMSR of the target OFC can be set according to the requirements. Based on the trained neural network, the operating parameters (V_1, V_2, V_{bias1}, V_{bias2}, P) can be designed easily. The OFC generated by using this parameter is highly consistent with the target OFC.

3. Network architecture

Firstly, obtain the data set. The OFC generator shown in figure 1(a) is simulated by using OptiSystem. The ranges of V_1 and V_2 are set as $-5 \sim 5$ V, V_{bias1} and V_{bias2} as $-15 \sim 15$ V, and P as $-10 \sim 10$ dBm. The results of literature [22] show that when the voltage upper limit is 5 V, only 7 comb lines with the flatness of 1.56 dB can be generated. Therefore, 9 comb lines of order -4 to order $+4$ are taken as our research objects. 100 000 sets of data are generated through uniform sampling. The data set is divided into three parts: training set (80%), validation set (10%), and test set (10%). The training set is used to adjust the weight and bias of each layer during training. The validation set is to make a preliminary evaluation of the model and judge whether the network is over-fitting. The test set is used to evaluate the generalization ability of the network after the training is completed.

Secondly, determine the network architecture. When there is too much training data, the nonunique input–output mapping may exist in the data set, which make the neural network difficult to converge [26]. Therefore, the cascaded network architecture as shown in figure 2 is adopted, which includes an inverse design network and a forward prediction network. The two networks both contain one input layer, four hidden layers, and one output layer. Through data learning and model tuning, the mapping relationship between target OFC and working parameters is established.

Thirdly, train the network. The first step is to train the forward network, which aims to accurately predict the power of each comb line from the working parameters and establish the mapping relationship between the working parameters and the spectrum. The input layer of the forward network has five nodes, representing each working parameter respectively. There are nine nodes in the output layer, representing the comb power respectively. By using the grid search method, the number of neurons in each hidden layer of the forward network is determined to be 128-256-256-128. The second step is to cascade the pre-trained forward network after the inverse network, and use the forward network to assist in training of the inverse network. Taking the power of the comb line as inputs, the inverse network generates a set of corresponding operating parameters, which is input into the forward network, and a spectrum is generated by using the forward network. Finally, the mean square error (MSE) between the target OFC and the generated spectrum is used as the loss function, and the weight and bias of each layer of the inverse network are optimized. The grid search method is also used to determine the number of neurons in each hidden layer, which is 128-256-256-128 respectively.

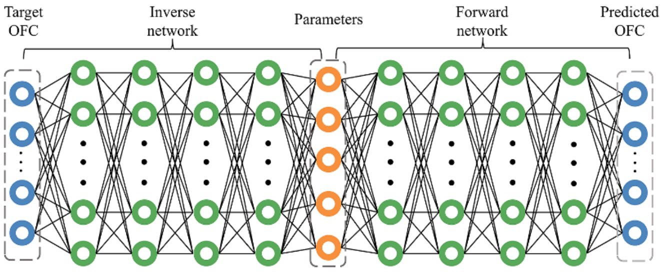

Figure 2. Architecture diagram of cascaded network for inverse design of OFC.

After testing, the trained network can show strong generalization ability, and the generated OFC is highly consistent with the target OFC.

4. Discussion

Using the constructed cascaded network, according to the target OFC, the operating parameters (V_1, V_2, V_{bias1},V_{bias2} and P) of the OFC are inversely designed. The programmability of comb-line number, comb power, SMSR, and comb spacing of OFC using deep learning-based inverse design method is studied. In the following research process, unless otherwise stated, the frequency of RF signal is 10 GHz, the comb-line number of the target OFC is set as 7, the average power of flat combs is -18 dBm, and SMSR is 5 dB.

4.1. Programmable comb-line number

When the target comb-line number is set as 3, 5, 7 and 9, the operating parameters of the OFC generator can be inversely designed by the constructed neural network, as shown in table 1. The corresponding spectrum is shown in figure 3, in which the blue lines represent the OFC simulated by OptiSystem and the yellow stars represent the target OFC. Figures 4, 6 and 8 are displayed in the same way.

As shown in figures 3(a)–(c), when the number of target comb lines is 3, 5, and 7, better flatness (<1 dB) can be obtained. When the upper limit of driving voltage is 5 V, the cascaded MZMs are used in [22] to generate 7 combs with the flatness of 1.56 dB. In this work, only a single DDMZM is used to generate 7 combs with a flatness of 0.40 dB. However, when the number of target comb lines increases to 9, the flatness deteriorates to 2.34 dB, as shown in figure 3(d). This is because the number of comb lines is related to the amplitude of the driving voltage, and the upper limit of the driving voltage is only 5 V, which limits the device to generate more comb lines. If the voltage is increased, more comb lines can be generated. In other words, if the device can generate a large number of comb lines physically, it is only necessary to modify the numbers of neurons in the input layer of the inverse network and the output layer of the forward network to the number of lines when constructing a cascaded network. After training, the proposed method can easily inversely design the case that the number of lines exceeds 9, without technical difficulties and impossibilities.

Table 1. Working parameters of different target comb-line number and flatness of OFC generated by these parameters.

Target	Inverse design					Simulation
Comb number	V_1 (V)	V_2 (V)	V_{bias1} (V)	V_{bias2} (V)	P (dBm)	Flatness (dB)
3	−0.34	0.42	3.25	6.96	0.27	0.26
5	−3.36	1.61	0.99	2.68	−3.02	0.61
7	−4.98	2.69	2.24	4.66	−1.83	0.40
9	−5.17	0.80	2.30	2.72	−0.05	2.34

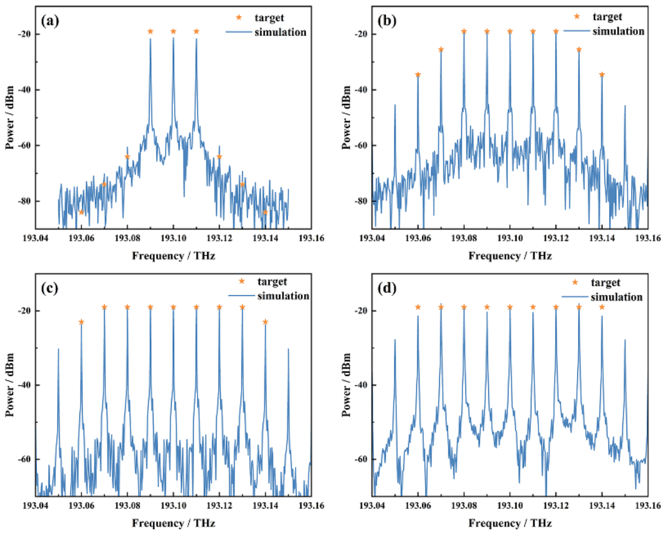

Figure 3. OFC generated by different target comb-line numbers: (a) 3; (b) 5; (c) 7; (d) 9.

Table 2. The average power and flatness of OFC are calculated by inversely designing the working parameters of different target comb power.

Target	Inverse design					Simulation	
Power/dBm	$-V_1$ (V)	V_2 (V)	V_{bias1} (V)	V_{bias2} (V)	P (dBm)	Power (dBm)	Flatness (dB)
−15	4.79	2.65	1.06	3.31	2.05	−14.83	0.40
−16	4.79	2.66	1.08	3.35	1.08	−15.87	0.36
−17	4.79	2.66	1.15	3.43	0.16	−16.82	0.33
−18	4.78	2.65	1.30	3.58	−0.82	−17.79	0.36

4.2. Programmable comb power

When the power of the target flat comb lines is set as −15, −16, −17, and −18 dBm, the working parameters obtained by the inverse design are shown in table 2, and the corresponding spectrum is shown in figure 4. It can be seen from table 2 that the average power (Power′) of flat generated comb lines is highly consistent with the target power (Power). When only the power of the target OFC changes, only the laser power changes significantly in the parameters of the inverse design. This shows that, in the case of target flatness and SMSR remain unchanged, the comb line power is mainly related to the laser power, which is consistent with the theory. At the same time, the flatness of OFC is almost unchanged at a good level (∼0.40 dB).

In addition, we further investigate the power programmability in a larger target comb-line power range. The power of the target flat comb is set from −32 dBm to −8 dBm with an interval of 1 dB. The relationship between the flatness of generated OFC and the target comb power is shown in figure 5. It can be seen, when the target power is in the range of −31 dBm ∼ −9 dBm, the flatness of OFC keeps at a good level (<1 dB). Therefore, the inverse design method for OFC using deep learning can realize the programmability of comb-line power within a certain range, that is, OFC with specified power can be generated according to the target, which avoids

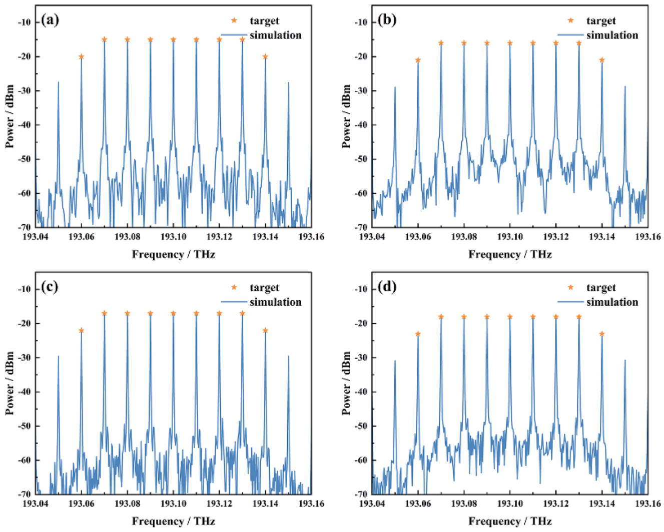

Figure 4. OFC generated by different target comb power: (a) −15 dBm; (b) −16 dBm; (c) −17 dBm; (d) −18 dBm.

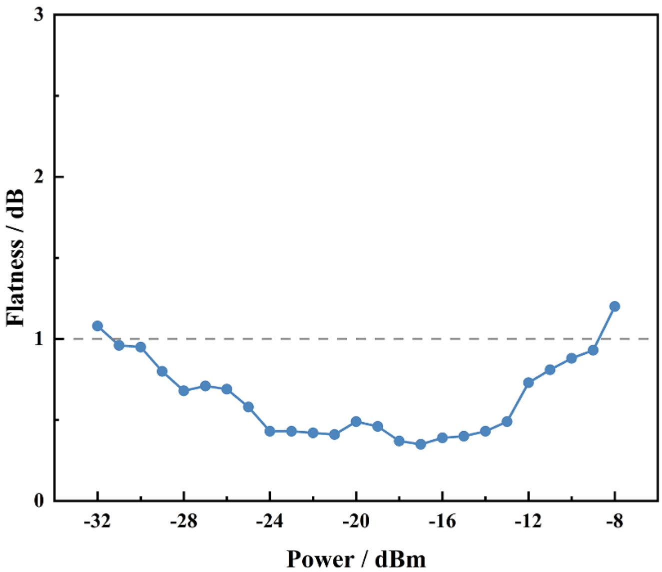

Figure 5. Influence of different target comb power on OFC flatness.

repeated debugging of laser power and improve the design efficiency.

4.3. Programmable SMSR

When the target SMSR is set as 4, 5, 6, and 7 dB respectively, the working parameters obtained by inverse design are shown in table 3, and the corresponding spectrum is shown in figure 6. The generated OFC can reach the pre-set SMSR, even slightly higher than the pre-set SMSR, which is also expectation. At the same time, the generated OFC is relatively flat (<1.5 dB).

To more comprehensively study the influence of target SMSR on the SMSR and flatness of generated OFC, we set the target SMSR as 4–9 dB, and obtained the relationship between the generated OFC and target OFC, as shown in figure 7. When SMSR is low (<6 dB), the designed OFC has good flatness (<1 dB). However, as the target SMSR increases, the flatness deteriorates. This indicates that in order to obtain an OFC with high SMSR, it is necessary to sacrifice a certain degree of flatness, which has guiding significance for the balance between SMSR and flatness. Therefore, by using the inverse design OFC method based on deep learning, SMSR programmability within a certain range can be achieved.

4.4. Programmable comb spacing

Theoretically, by changing the frequency of RF signals, the comb spacing of generated OFC can be tuned [25]. The target comb line power is set to −18 dBm, and the corresponding working parameters are shown in table 2. The frequency of the RF signal is set to 5, 10, 15 and 20 GHz respectively and the corresponding spectrum is shown in figure 8, which has the

Table 3. The working parameters of different target SMSR are inversely designed, and the SMSR and flatness of generated OFC are calculated.

Target	Inverse design					Simulation	
SMSR/dB	$-V_1$ (V)	V_2 (V)	V_{bias1} (V)	V_{bias2} (V)	P (dBm)	SMSR (dB)	Flatness (dB)
4	4.99	2.56	1.98	4.11	−0.83	4.50	0.35
5	4.78	2.65	1.30	3.58	−0.82	5.51	0.39
6	4.62	2.70	0.90	3.18	−0.91	6.16	0.92
7	4.49	2.68	0.96	3.25	−1.02	7.39	1.40

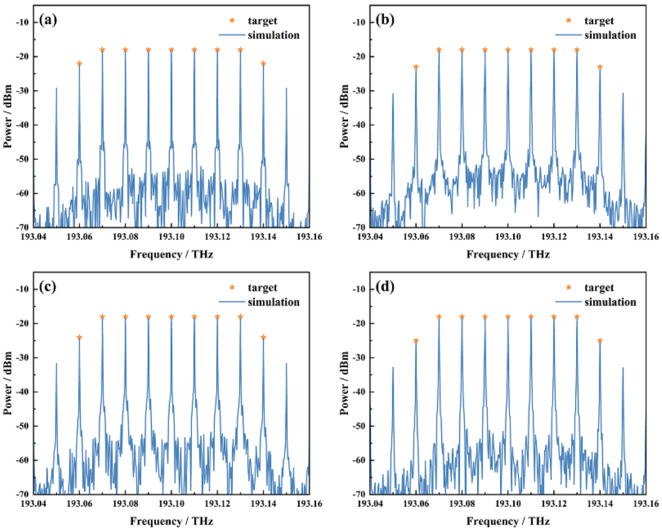

Figure 6. OFC generated by different target SMSR: (a) 4 dB; (b) 5 dB; (c) 6 dB; (d) 7 dB.

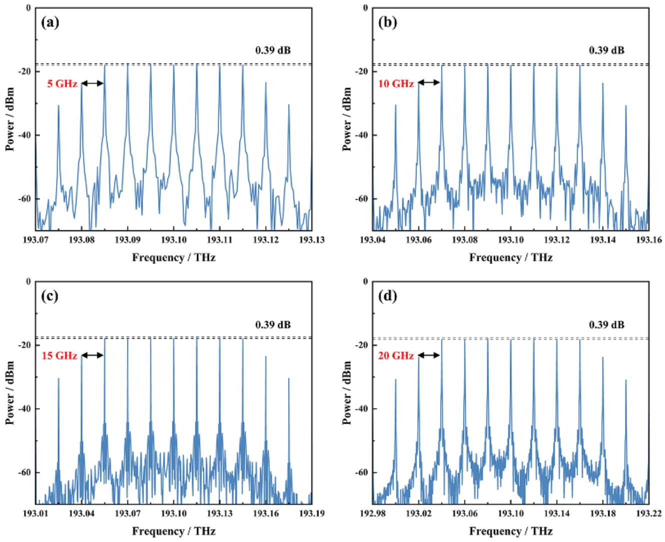

Figure 8. OFC generated with different comb spacing: (a) 5 GHz; (b) 10 GHz; (c) 15 GHz; (d) 20 GHz.

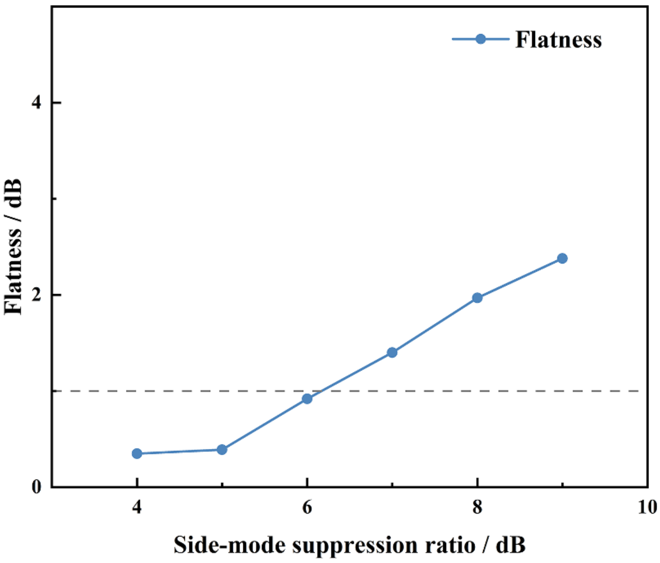

Figure 7. The relationship between the target SMSR and the flatness of generated OFC.

comb spacing of 5, 10, 15 and 20 GHz respectively. Just as we expected, the flatness remained almost unchanged. Therefore, the comb spacing of OFC can be adjusted by changing the frequency of the RF signal, which is consistent with the theory.

5. Conclusion

In this paper, we propose an inverse design method of programmable OFC based on deep learning and apply it to an OFC generator based on a single DDMZM driven by a single RF signal. We use OptiSystem software to validate our proposed method. The research results show that the method of inverse design for OFC based on deep learning can obtain the corresponding working parameters in real time according to the target OFC. It not only solves the problem that the traditional control variate method requires continuous trial and error, but also overcomes the shortcoming that the optical comb generation method based on the optimization algorithm cannot be real-time, and shows its powerful application potential. In addition, the designed OFC based on deep learning can realize the programmability of the comb-line number, comb-line power, SMSR, and comb spacing, which solves the problem of lack of programmability in the existing OFC generation technology. The designed OFC has good flatness (<1 dB) and can generate 7 flat comb lines with a flatness of 0.33 dB. If supplemented by a control system, the intelligence of the programmable OFC based on deep learning can be improved. This method can be extended to the case of cascaded modulators and multiple RF signal, and even to more complex OFC generators. We believe that this method can free researchers from tedious parameter tuning work to focus on more esoteric mechanistic studies. In addition, if the experimental data is used as the dataset, the target OFC can be easily obtained in the experiment by using this deep learning-based inverse design method.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Acknowledgments

This work was supported by the Postgraduate Research & Practice Innovation Program of Jiangsu Province (under Grant No. 46006CX21277)

ORCID iD

Yunjie Ma https://orcid.org/0000-0001-5788-7202

References

[1] Zhang L, Lu P, Chen L, Huang C, Liu D and Jiang S 2012 *Opt. Lett.* **37** 2622
[2] Rutkowski L, Masłowski P, Johansson A C, Khodabakhsh A and Foltynowicz A 2018 *J. Quant. Spectrosc. Radiat. Transfer* **204** 63
[3] Alshaykh M S, McKinney J D and Weiner A M 2019 *IEEE Photonics Technol. Lett.* **31** 1874
[4] Liu Y, Gao H, Chen Y and Li P 2020 *Opt. Fiber Technol.* **58** 102252
[5] Fan Y M and Li P L 2020 *Opt. Eng.* **59** 1
[6] Endo M, Shoji T D and Schibli T R 2018 *IEEE J. Sel. Top. Quantum Electron.* **24** 1
[7] He X, Zhang P, Zhang Y, Lin Q, Guo H, Hou L and Wang K 2020 *Front. Phys.* **8** 226
[8] Weng H, Huang Y, Yang Y, Xiao J, Han J and Liao M 2017 *Asia Communications and Photonics Conf. (ACP)* pp 1–3 (available at: https://ieeexplore.ieee.org/document/8649331/references#references)
[9] Goji Y, Chen C, Ikeda K, Yoshii K and Hong F-L 2021 *Results Opt.* **2** 100035
[10] Li J, Qu Y, Yu R and Wu Y 2018 *Phys. Rev.* A **97** 023826
[11] Buscaino B, Zhang M, Lončar M and Kahn J M 2020 *J. Lightwave Technol.* **38** 1400
[12] Wang M and Yao J 2013 *IEEE Photonics Technol. Lett.* **25** 2035
[13] Ullah R, Ullah S, Khan G Z, Mao Y, Ren J, Zhao J, Chen S, Li M and Khan J 2021 *Results Phys.* **22** 103849
[14] Gheorma I L and Gopalakrishnan G K 2007 *IEEE Photonics Technol. Lett.* **19** 1011
[15] Yang Y, Ma J, Xin X, Zhang Q, Zhang Y, Yin X, Zhang R and Liu W 2016 *Photon. Netw. Commun.* **32** 126
[16] Shang L, Wen A and Lin G 2014 *J. Opt.* **16** 035401
[17] Sakamoto T, Kawanishi T and Izutsu M 2007 *Electron. Lett.* **43** 1039
[18] Sakamoto T, Kawanishi T and Izutsu M 2007 *Opt. Lett.* **32** 1515
[19] Yokota N, Abe K, Mieda S and Yasaka H 2016 *Opt. Lett.* **41** 1026
[20] Hmood J K and Harun S W 2018 *Opt. Fiber Technol.* **42** 75
[21] Francis H, Zhang X D, Chen S, Yu J W, Che K J, Hopkinson M and Jin C Y 2021 *IEEE J. Sel. Top. Quantum Electron.* **27** 1
[22] Pendiuk G F I, Neves P T and Pohl A A P 2020 *OSA Contin.* **3** 2232
[23] Pendiuk G F I, de Tarso Neves P and Pohl A D A P 2018 *Frontiers in Optics / Laser Science* JW3A–82
[24] Pinto T, de Moura U C, Da Ros F, Krstic M, Crnjanski J V, Napoli A, Gvozdic D M and Zibar D 2021 *Opt. Express* **29** 23447
[25] Xie H L, Jia K X, Chen J W, Fan Y M and Li P L 2020 *Chin. J. Lasers* **47** 374
[26] Liu D, Tan Y, Khoram E and Yu Z 2018 *ACS Photonics* **5** 1365