

Research Article

High-Efficiency Mitigation of Nonlinear Distortion in Microwave Photonics Link Assisted by Artificial Neural Network

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A microwave photonics radio over fiber link can deliver the radio frequency (RF) signal to realize the antenna remote. When the signal is a broadband and multicarrier RF signal, there are some linear distortions in the link, such as the crossmodulation distortion (XMD) and third-order intermodulation distortion (IMD₃). It will destroy the wide-bandwidth performance of the link. Traditional postdigital compensation methods for XMD and IMD₃ mitigation extract the baseband signal and reconstruct the compensation signal with calculated compensation factor. Here, a kind of artificial neural network genetic algorithm (ANN-GA) distortion compensation technique is proposed to seek the compensation factor instead of calculations. The neural network algorithm is used to fit the mapping function between the compensation factor and the distortion and give a set of predicted data as the original individual fitness value for the genetic algorithm. Based on the original value, the minimal distortion, the corresponding optimal compensation factors γ and α are found with optimization iterations. Taking advantage of the optimal compensation factors, based on the traditional postdigital compensation method, the distortion is mitigated with a suppression ratio of -84.4 dB. In our paper, the mitigation technology of the XMD and IMD₃ can be applied for any kinds of link instead of mathematically modelling the link and calculating the compensation factor. The technology can improve the intelligence and flexibility of microwave photonic link linearization design.

1. Introduction

With the development of the communication and radar applications, the demand for bandwidth is growing, which increases the complexity for the transmission, processing, and reception of the ultrabroadband, multicarrier RF signal based on the traditional electrical technology. However, the rapidly developing photonic technology will be a prospective analog signal processing platform. The microwave photonics technique combines the microwave and photonics and occupies both microwave advantage of precise spectrum processing and the photonics property of wideband, low loss, and strong immunity to electromagnetic interference [1]. The merits make the microwave photonics technology efficiently process the complex RF signals in microwave systems. In recent years, many kinds of multiple carrier radio over fiber (ROF) links are designed to realize the RF signal transmission and down-

conversion. In radar and electronic countermeasure applications, the ROF link links the antenna and the data process center for getting the greater mobility and stronger resistance to damage. It is worth to note that the wideband, high sensitivity, and large dynamic range property of link are the key factors for improving the radar detection range and resolution [2]. However, there are some nonlinear distortion such as third-order inter modulation distortion (IMD₃) and crossmodulation distortion (XMD) deteriorating the dynamic range. Nonlinear distortion in ROF link is frequently introduced by the nonlinear response in laser, modulator, and detector. To solve the distortion problem in links, many kinds of linearization techniques are applied to the links. Some of the distortion mitigation methods are proposed by doing several designs in the modulation, such as constructing the cascaded or parallel electrooptic modulators [3–8]. In those designs, the two Mach-Zehnder modulators (MZMs) operate at

the opposite slope of the transfer functions to obtain the opposite phase of IMD_3 signal and cancel each other. In addition, electronic predistortion compensation [9, 10], feed-forward compensation [11, 12], and postdistortion compensation [13–17] are also important means. In digital compensation schemes, the digital processor circuit is designed to sample and extract the correction signal to suppress the distortion. For example, in postlinearization link, the correction signal is extracted by filters and processed in digital signal processor (DSP) to get the distortion compensation signal to suppress the link distortion. A typical postdistortion compensation link has demonstrated at least a 25 dB distortion suppression by a combination of electrooptics, microwave circuitry, and digital signal processing. In multiple-channel ROF links, the input signal is a broadband RF signal that consisted of multiple frequency components, so that the link linearity is deteriorated by not only IMD_3 but also by XMD. In [18], the XMD is suppressed by predistortion. In [19], the XMD is mitigated with postdistortion compensation. However, there are some weaknesses in the traditional digital distortion compensation. For example, the digital signal process is based on the precise mathematical model of the link. On the one hand, the present ROF link model is derived in small signal condition, which will be failed when the modulation depth is deeper. On the other hand, the mathematical model needs to be rederived according to variable link structures.

Artificial intelligence microwave photonics technique is an emerging direction in microwave photonics. The artificial neural network (ANN) has made tremendous progress contributing to the abilities of self-study, associate storage, high-speed search for the best solutions, and drawing arbitrarily complex nonlinear relationships. In recent years, the ANN is applied to the microwave photonics field to enhance the system performance [20–22]. Defining the input and output variables of a microwave photonics link, the link is mathematically viewed as a nonlinear function. Thus, by training the ANN with input and output data of the microwave photonics link, the ANN can fit the nonlinear mapping of the microwave photonics link. Then, the trained ANNs can predict the link function instead of deriving the mathematical model.

Combining the traditional digital distortion compensation method and the artificial neural network genetic algorithm (ANN-GA), a kind of ANN-GA-based distortion compensation technique is proposed for multicarrier downconversion microwave photonics link (MDC-MWPL) distortion mitigation. The traditional downconversion microwave link with the postdistortion compensation is composed of the laser, modulator and photodiode, analog digital converter (ADC), and a digital signal process (DSP). Based on the traditional link, the ANN-GA is added and realized by DSP. In the digital circuit, correction signal is extracted by the passband filter to reconstruct the compensation signal with the compensation factors γ and α , which are sought by the ANN-GA. The distortion XMD and IMD_3 will be eliminated with a suppression ratio great than -84.4 dB.

2. Principle of the Digital Distortion Compensation Process

2.1. Principle of the XMD Compensation. The schematic diagram of the proposed MDC-MWPL is shown in Figure 1. The light signal is generated by the laser and transmitted into modulator 1. The polarization controller between the laser and modulator 1 is used to adjust the light signal polarization state to be consistent with the modulator spindle. The RF signal is modulated to the light signal in modulator 1. Then, the output light signal from modulator 1 is delivered to modulator 2 and modulated by a local oscillator (LO) signal. The photodiode (PD) converts the modulated light signal to electric signal and achieves downconverting the RF signal to the IF signal. The IF signal is sampled by the ADC module and converted to digital signal. Within the digital domain, by using the digital filters, the correction signals are extracted to reconstruct the compensation signal. In the DSP, the trained artificial neural network establishes the map relationship between the compensation factor and the distortion and gives the prediction values of the XMD, IMD_3 , and the corresponding γ and α . With the normalization of the given compensation factor data and the reverse normalization of the prediction, the prediction values fill the role of the original fitness value in the genetic algorithm. Based on the original fitness value, the genetic algorithm will find the minimal fitness value (minimal distortion) and the corresponding compensation factors γ and α . Then, compensation signal with distortion mitigation is reconstructed using the compensation factors γ and α .

The sampled signal by the ADC module is extracted by narrow band-pass and low-pass digital filters and divided into two correction signals, denoted as signal 1 (S_1) and 2 (S_2), respectively. The two signals are used to construct a compensation signal to suppress the XMD and IMD_3 . The signal processing for XMD mitigation is shown in Figure 2. To explain the signal processing mechanism, the process is expressed by the mathematically analytical method. Mathematically, the broadband multicarrier RF signal, denoted as $x(t)$, can be written as Equation (1), which is a sine function with a center frequency of ω_n , amplitude of $A_n(t)$, and the phase of $\phi_n(t)$.

$$x(t) = \sum_n A_n(t) \cos(\omega_n t + \phi_n(t)). \quad (1)$$

For an intensity modulation with direct detection link, the transfer function can be expanded in terms of the Tyler function as follows:

$$P(t) = a_0 + a_1 x(t) + a_2 [x(t)]^2 + a_3 [x(t)]^3 + \dots \quad (2)$$

Equation (2) contains the higher order distortion terms, such as $[x(t)]^2$ and $[x(t)]^3$. To extract the correction signal, the expression of the RF signal recovered from the PD is

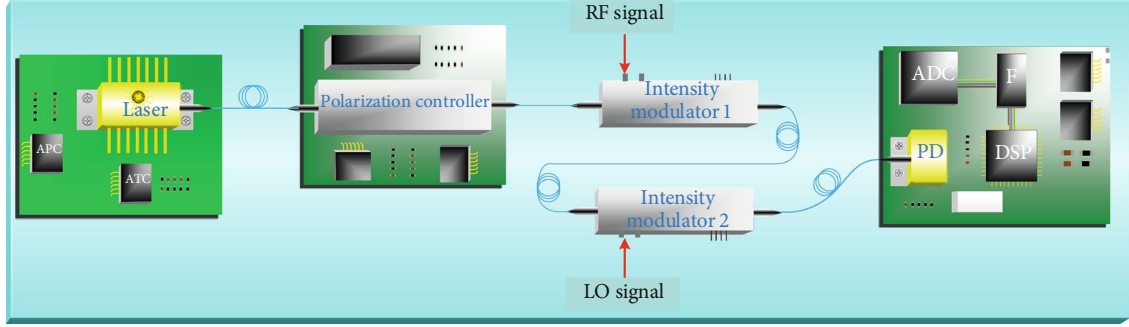


FIGURE 1: The multicarrier downconversion microwave photonics link with the DSP circuit for mitigating the nonlinear distortion.

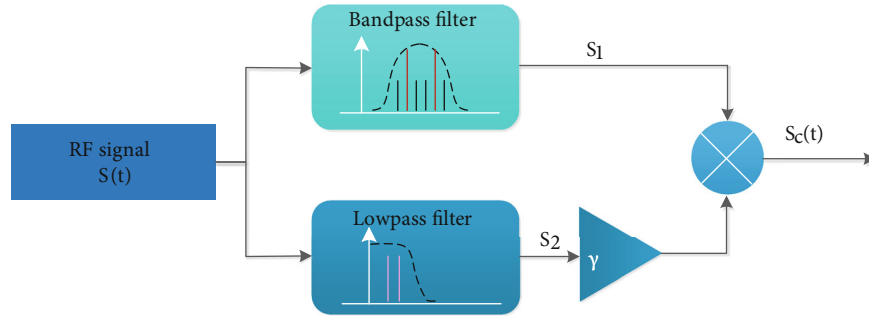


FIGURE 2: The diagram of the signal processing of reconstructing the compensation signal for XMD mitigation.

deduced by inserting Equation (1) into Equation (2).

$$\begin{aligned}
 S(t) &= a_0 + a_1 \sum_n A_n \cos \omega_n t + a_2 \left(\sum_n A_n \cos \omega_n t \right)^2 \\
 &+ a_3 \left(\sum_n A_n \cos \omega_n t \right)^3 + \dots \approx a_0 + a_2 \sum_n A_n^2 \\
 &+ \sum_n \left[a_1 + a_3 \left(A_n^2 + \sum_m A_m^2 \right) \right] A_n \cos \omega_n t,
 \end{aligned} \quad (3)$$

where $\sum_m A_m^2(t)$ and $\sum_n A_n^2(t)$ are XMD and IMD term, respectively. We define the correction signal as the S_1 and S_2 :

$$S_1 = \sum_n \left[a_1 + a_3 \left(A_n^2 + \sum_m A_m^2 \right) \right] A_n \cos \omega_n t, \quad (4)$$

$$S_2 = a_0 + a_2 \sum_n A_n^2, \quad (5)$$

where S_1 and S_2 contain the XMD and IMD_3 , respectively. To extract the baseband signal S_1 and S_2 to construct the compensation signal, the digital filter is designed. S_1 and S_2 are filtered by the band-pass filter and low-pass filter, respectively. Then, the compensation signal for XMD mitigation is obtained as follows:

$$S_c(t) = S_1 * S_2^\gamma, \quad (6)$$

where γ is the XMD compensation factor. As shown in Figure 2, based on the digital signal process, the constructed compensation signal $S_c(t)$ is generated, and the XMD in $S_c(t)$ is mitigated. With traditional methods, the compensation factor γ is calculated by further solving the link mathematical small signal model, which is inapplicable to big signal drive link. To further optimize the distortion mitigation performance, a novel method to seek the compensation factor based on ANN-GA is proposed in Section 3.

2.2. Principle of the IMD_3 Compensation. In the compensation signal $S_c(t)$, the XMD is mitigated, while the IMD_3 still exists in signal $S_c(t)$. The IMD_3 is the largest odd distortion term in link, which is close to the main signal. To mitigate the IMD_3 , the operation on signal S_1 is made to generate the signal $S_D(t)$ as follows:

$$S_D(t) = 1 + \alpha S_1^2, \quad (7)$$

where α is the IMD_3 compensation factor. Then, $S_D(t)$ is divided into $S_c(t)$ to construct a compensation signal $S_L(t)$ to suppress the IMD_3 :

$$S_L(t) = \frac{S_D(t)}{S_c(t)} = \frac{1 + \alpha S_1^2}{S_c(t)}. \quad (8)$$

The whole flow chart is shown in Figure 3, in which the compensation flow consists of two main parts: XMD mitigation and IMD_3 mitigation. Both in the two parts, the

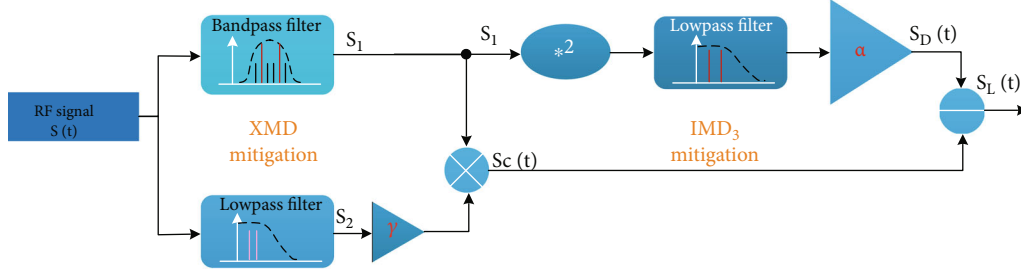


FIGURE 3: The diagram of the signal processing of reconstructing the compensation signal for IMD_3 mitigation.

compensation factors γ and α are key variables, which are sought by the ANN-GA introduced in Section 3.

3. Principle of the Distortion Mitigation Optimization Based on the ANN-GA

According to the principle of the XMD and IMD_3 compensation, the key factors which dominate the performance of distortion mitigation are γ and α . In traditional methods, the γ and α are obtained by mathematical equation, which contains the variables such as modulator bias point and the output 3rd intermodulation point. Specifically, the accurate values of γ and α are calculated by solving the transfer function of link based on the small signal condition. However, in fact, different components, link structures, and operation conditions have variable link transfer functions. On the one hand, it needs to solve the link transfer function; on the other hand, the solved function cannot exactly fit the link in some situations, such as big signal drive. To intelligitize the compensation and improve the distortion mitigation ratio, the ANN-GA is proposed.

The process of seeking compensation factors γ and α based on the ANN-GA is divided into two main steps: Step 1: train backpropagation (BP) neural network, and predict the output of the link, and Step 2: seek the values of γ and α and the corresponding minimal values of XMD and IMD_3 by genetic algorithm. The detail flow is shown in Figure 4. The neural network prediction contains the network structure construction, data initialization, neural network training, test, and prediction. In the training process, the training times depend on the epochs and network targets, which is the termination condition (1). The genetic algorithm optimization contains the population initialization, individual fitness calculation, seeking optimal individual, selection operation, crossover operation, mutation operation, iteration, and updating optimal individual. The process from fitness calculation to mutation represents the evolution. Every time evolution will find the best fitness and replace the last fitness until the set generations are reached, which is the termination condition (2).

The BP neural network is one of the most widely used neural network models. It can learn and store a large number of input-output mapping without prior knowledge of the mathematical function equations. The BP network is composed of input layer, hidden layer, and output layer, in which each layer is composed of many parallel neurons. The neurons between

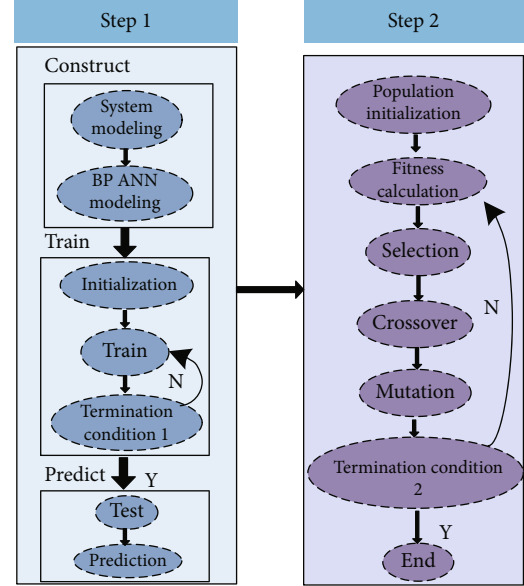


FIGURE 4: The flow chart of the ANN-GA.

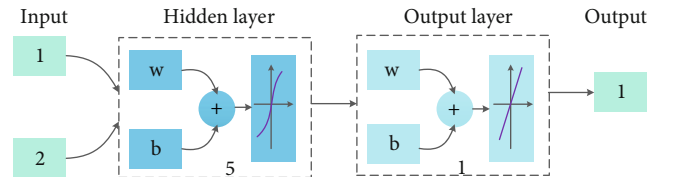


FIGURE 5: The structure of the neural network.

different layers are connected. But there is no mutual connection between the neurons of the same layer. Here, the compensation factors γ and α are identified as the inputs and the power level of XMD and IMD_3 as the outputs of the neural network. The prediction accuracy of the neural network is the key factor for the genetic algorithm to find the optimal compensation factors and the corresponding minimal XMD and IMD_3 . The learning capability of the BP neural network is closely related to its structure, because the memory capacity of the network, the speed of training, and the amount of response depend on the structure, which corresponds to the number of hidden layers and nodes. According to the Kolmogorov theory, as long as there are enough hidden layer nodes, the neural network can approach a nonlinear function. A continuous function $F(x)$ in the closed intervals can be precisely implemented with a three-layer neural network, where the

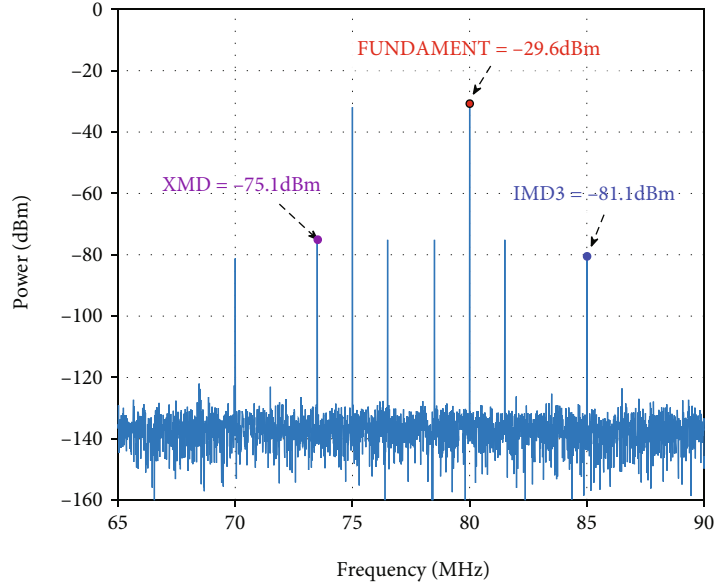


FIGURE 6: The output spectrum of the link without compensation.

number of nodes in the input layer is M , the number of nodes in the hidden layer is $K = 2M + 1$, and the number of nodes in the output layer is N . In fact, the number of nodes would be increased with the number of samples increasing. Here, we select the compensation factors γ and α as the inputs ($M = 2$, $K = 5$). And the output can be switched between XMD and IMD_3 . So $N = 1$. The neural network structure is “2-5-1” type, as shown in Figure 5.

In the genetic algorithm, we need several iterations to find the optimal individual. For each iteration, the optimal individual is updated by conducting the selection, the crossover, and the mutation operations. Firstly, the original individual fitness value comes from the prediction of the BP neural network. The individual in the genetic algorithm is encoded as a real number, and the length of the individual depends on the number of the link output variables. If there are two variables, the length of the individual is 2. Then, the individuals that are more suited to the environment are selected to multiply the next generation from a group. The smaller the fitness value, the better the individual. Different from the selection, the two new individuals will be born after one crossover, which are used to seek the new point in group space. The mutation simulates the accidental process in natural genetic environment. If there are only selection and crossover, genetic algorithm cannot search the space beyond the initial gene combination, and the evolution process easily falls into the local solution. According to the optimization goal, the probability of crossover and mutation is set as needed.

4. Simulation Results and Analysis

To verify the theory, we design the simulation experiment. The link output spectrum without compensation is simulated in MATLAB, and the link structure is shown as Figure 1. In the simulation, the RF main signal is a dual-

tone signal with the frequency interval of 5 MHz, at the frequency of 15 GHz and 15.005 GHz, respectively. The out-band crosstalk signal is represented with a dual-tone signal with the frequency interval of 1.5 MHz, at the frequency of 3 GHz and 3.0015 GHz, respectively. The local oscillator signal is introduced to downconvert the RF signal to the IF signal at the frequency of 75 MHz and 80 MHz, respectively. The switching voltage of modulator, the effective responsivity of the PD, and the input optical power of the PD are set to 6 V, 0.9A/W, and 5 dBm, respectively. The output spectrum of the link without compensation is shown in Figure 6. As we can see, the IF signals are seriously interfered by XMD signals with the power of -75 dBm, at the frequency of 73.5 MHz, 76.5 MHz, 78.5 MHz, and 81.5 MHz, respectively. At the same time, the IF signals are interfered by IMD_3 signal with the power of -81.1 dBm, at the frequency of 70 MHz and 85 MHz, respectively.

To get the appropriate compensation factors γ and α , the BP neural network is trained using 5000 sets of data, in which each set of data consists of two inputs (γ and α) and two outputs (XMD and IMD_3). And 500 sets of data are used to test the fitting effect of the BP neural network. The deviation of the outputs predicted by BP neural network and the outputs expected is calculated:

$$\kappa = \text{XMD}_{\text{pre}} - \text{XMD}_{\text{exp}}, \quad (9)$$

where the XMD_{pre} and XMD_{exp} are prediction and expectation values of the XMD and IMD_3 , respectively. According to Equation (9), the calculated results are shown in Figure 7. The XMD deviation ranges from -0.04 dB to 0.06 dB, which demonstrates a precise prediction of the BP neural network. The IMD_3 deviation mostly ranges from -2 dB to 2 dB. However, at some points, the deviation is up to 7 dB, which means that the BP neural network should

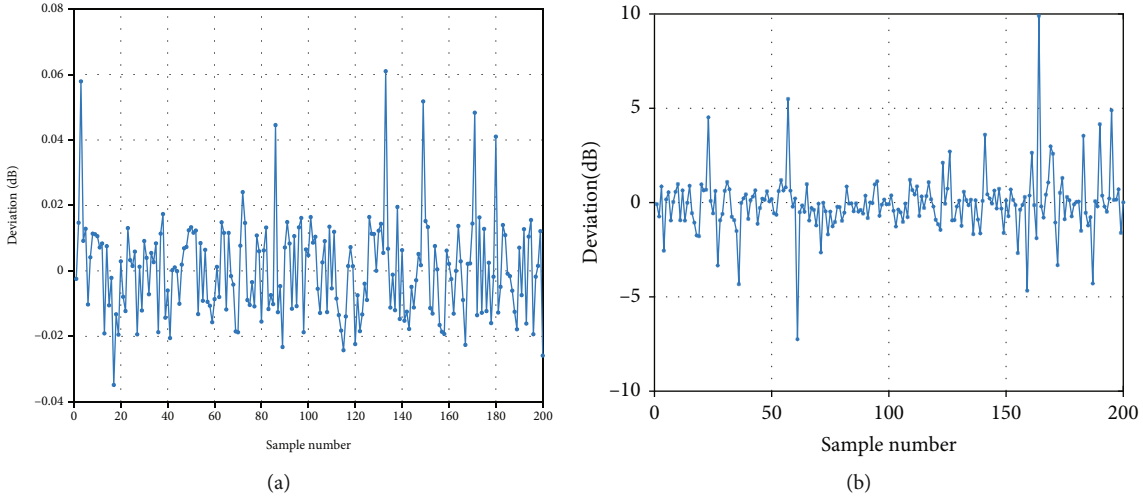


FIGURE 7: The prediction deviation of the trained ANN versus the number of samples: (a) for the XMD; (b) for the IMD₃.

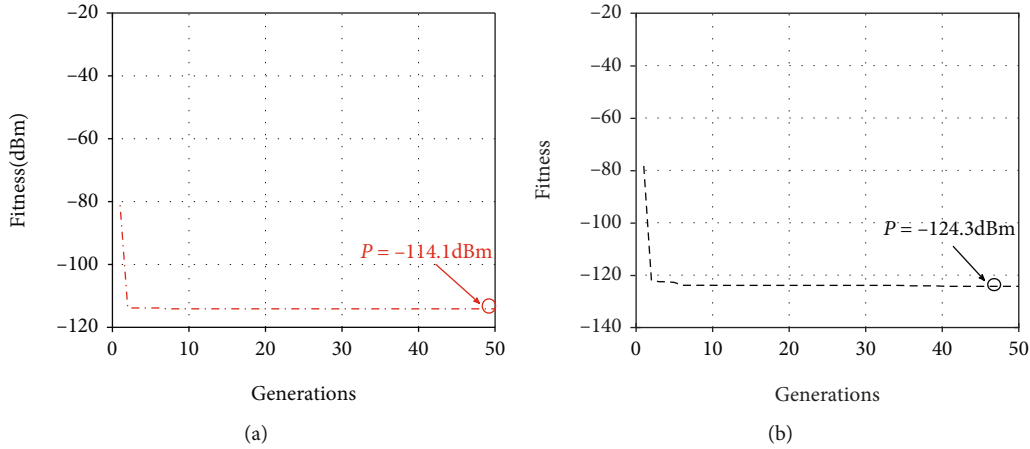


FIGURE 8: The fitness evolution curve versus the number of generations: (a) for XMD as the fitness; (b) for IMD₃ as the fitness.

ulteriorly improve the neural structure or enlarge the number of the sample.

From the calculated deviation results, in general, the ANN can accurately predict the output of the link. So, the predicted output can be approximately regarded as the actual output of the link.

After the BP neural work training, the genetic algorithm is used to seek the compensation factors γ and α and the corresponding optimal values of the XMD and IMD₃. The outputs of the BP neural work are used as the original individual fitness value of the genetic algorithm. The generation number, the population size, the crossover, and the mutation probability are set to 50, 20, 0.4, and 0.2, respectively. The evolution curve of the optimal individual fitness value in the optimization process is shown in Figure 8. From the evolution curve, the optimal individuals, XMD and IMD₃, are -114.1 dBm and -124.3 dBm, respectively, and the corresponding factor γ and α are -2.1 and 2980, respectively.

Then, the compensation process is added at the end of the link. To verify the compensation effect, the predicted

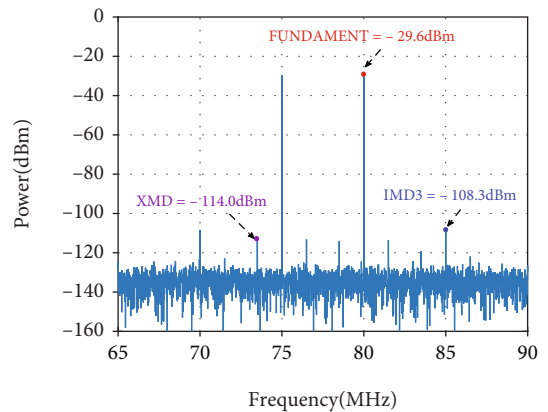


FIGURE 9: The spectrum of the link with the digital compensation applying the optimal compensation factor.

compensation factors are applied to the link to simulate the spectrum in MATABL. In the simulation experiment, the parameters are the same as the parameters in Figure 6 beside adding the compensation factors γ and α . The

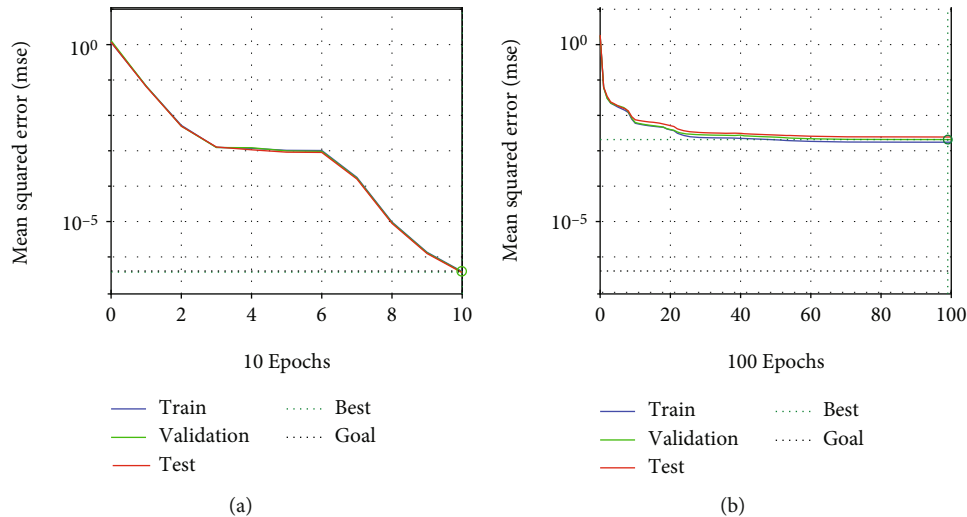


FIGURE 10: The mean square error in the BP algorithm versus the epochs for different nonlinear mapping: (a) for compensation factors as input and XMD as output: (b) for compensation factors as input and IMD_3 as output.

simulated spectrum with distortion mitigation based on the ANN-GA is shown in Figure 9. As we can see, the XMD and IMD_3 power level is about -114.0 dBm and -108.3 dBm, respectively. And the power level of XMD in Figure 9 is consistent with the predicted XMD in Figure 8(a). However, the IMD_3 in Figure 9 is 16 dB higher than the IMD_3 in Figure 8(b), which shows several differences between the prediction and simulation experiment.

Furthermore, to find the cause of the decline of prediction accuracy, the detailed discussion and analysis are conducted. The reason why prediction result of the IMD_3 shows the less precision may be that the prediction precision depends on the sample number and neural network structure. On the one hand, for the sample number, we add the sample number to 50000 and train the neural network. However, the prediction precision has no improvement. On the other hand, for the neural network, the BP neural network shows the limitation in fitting the complex nonlinear function. The BP neural network is based on the gradient descent algorithm, which means that the network relies on the instantaneous gradient value of the error curved surface. Due to the complex nonlinear mapping between the compensation factors γ and α and the IMD_3 , there are some flat areas on error curved surface, where the error gradient changes slowly. To quantitatively analyze the changing process, the mean square error is expressed as follows:

$$\text{MSE} = \frac{1}{n} \sum_n (D_{\text{exp}} - D_{\text{pre}})^2, \quad (10)$$

where D_{exp} and D_{pre} are expectation and prediction value, respectively. As shown in Figure 10, the curves exhibit the mean square error changes versus the epochs. For the IMD_3 prediction, between the 20 and 100 epochs, the error falls slowly, shown in Figure 10(b), because there are many minimum points in the error curved surface for complex nonlinear function. And the minimum point will

prevent BP neural network adjusting the weight to iterate effectively. The principle behind the weight adjustment is that the error gradient should be decreasing after adjusting the weight. However, the error gradient will be greater than zero once away from the minimum point. So it is the reason why the mean square error decreases slowly with the number of training sample increasing. In other words, the BP neural network gets into the local optimum. In the following research, we should change the BP algorithm. Conventional BP neural network only uses the gradient error to adjust the weight, that is, the information of the first derivative, while we can use the second derivative information to adjust the weight. The basic idea is that each iteration no longer follows a single negative gradient direction but follows the error to search along the direction of deterioration.

5. Conclusion

In this work, a microwave photonic link linearization technique is proposed by combining the traditional microwave photonic link digital distortion mitigation method and the artificial neural network. The recovered RF signal from the PD is digitized and filtered by band-pass and low-pass filters. The compensation signals are reconstructed by the signal process using the compensation factors and the filtered signal, where the compensation factors are obtained by the ANN-GA that consisted of BP neural network and genetic algorithm. The BP neural network learns the input-to-output mapping of the link and predicts the output value as the individual fitness value of the genetic algorithm. Based on the fitness value, the optimal compensation factors γ and α are found by the genetic algorithm. The simulation experiment shows that the power level of the mitigated XMD and IMD_3 is -114.0 dBm and -108.3 dBm, respectively. The combination of the artificial neural network and microwave photonics provides a new idea for the design of high-performance microwave photonics link. Different from the

traditional digital distortion compensation, the proposed technique can realize distortion compensation for any kinds of links and is independent of microwave photonics link structure and corresponding mathematical model. So it improves the intelligence and flexibility of microwave photonic link linearization design. However, it is worth to note that the BP neural network shows slightly insufficiently in fitting the complicated nonlinear link. So, developing more advanced and matched neural network may be the research hotspot for the intelligence microwave photonics.

Data Availability

All data included in this study are available upon request by contact with the corresponding author.

Disclosure

An earlier version of this work was presented as a conference paper at AICON 2021 [23].

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Yihui Yin and Wanli Yang are co-first author.

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