

Reservoir Computing Based Equalization for Radio over Fiber System

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Abstract—Reservoir computing (RC) attracts much attention in many time-series tasks due to its nonlinear mapping capability from the lower space to the higher space and the dynamic memory ability. With conceptual simplicity and computation cheapness, RC is also suitable for hardware implementation. In this paper, the RC is applied to perform the signal equalization for wavelength division multiplexing (WDM) radio over fiber (RoF) system to compensate the distortion caused by the nonlinearity of single wavelength and the interference between multiple wavelengths. Simulation results show that RC with 500 reservoir nodes can enhance the adjacent channel power ratio (ACPR) of the WDM-RoF system from 6 dB to 9 dB after equalization, where the ACPR can be further improved by simply increasing the reservoir size.

Keywords—Reservoir Computing, Equalization, Wavelength Division Multiplexing, RoF, Distortion, Adjacent Channel Power Ratio

I. INTRODUCTION

The Radio over fiber (RoF) network is a promising technique for providing broadband and high capacity wireless communication services, which contains both optical and electrical component. Due to the low attenuation of fiber, the radio frequency (RF) signals can be delivered from the central unit (CU) to the remote radio unit (RRU) over long distance without requiring regenerating equipment. Meanwhile, the baseband digital signal processor, digital to analog convertor, analog to digital converter, mixer, frequency conversion devices and filters can be removed from the RRU to the CU, which highly reduces the complexity and energy consumption of RRU [1]. Combined with the reconfigurable antenna array design, tunable filters and multiplexing techniques, the RoF system has the ability to deliver signals with different formats (from baseband digital signals to mmWave RF signals) simultaneously [2]. In order to further enhance the cell coverage and throughput, the RoF is upgraded with wavelength division multiplexing (WDM) technique, which is called WDM-RoF system [3].

Besides the linear distortion such as fiber attenuation and

chromatic dispersion, the RoF/WDM-RoF system also suffer from the signal nonlinear impairments caused by the Kerr effect and the inelastic scattering. Investigation results suggest that, those nonlinearity are mainly introduced by the electrical and optical (EO/OE) convertors, fiber, optical amplifier, etc.

So far, several techniques, such as the linear system with nonlinear components (LINC), digital back propagation, phase conjugation technique, digital pre-distortion (DPD) are investigated for reducing the nonlinearity in the RoF/WDM RoF system [4]. Among those techniques, DPD has been extensively discussed for RoF system [5], yet it is seldom mentioned for WDM-RoF system [6]. Considering the nonlinearity of single wavelength and the interference between multiple wavelengths in the WDM-RoF system, the equalization techniques, which already exhibit strong compensation ability in the RF MIMO system [7], also can be introduced to the WDM-RoF system.

Recently, the artificial neural networks (ANNs) has been intensively studied for various applications, including the channel estimation [8–11]. The ANN is able to be utilized in modelling nonlinear phenomenon of channel estimation, as it has the ability to form arbitrarily shaped nonlinear decision boundary regions [12]. Besides, it can perform complex mapping between the input and the output space. Two different ANN structures, namely multilayer perceptron (MLP) and recurrent neural network (RNN) have been trained and tested for wireless channels. The former is mainly feedforward neural networks architecture, while the latter exhibits dynamic behaviour due to feedback connections in architecture and has the capability to store nonlinear transformations of the input history in its internal state, resulting in dynamical memory. Thus, RNN has superior estimation performance for its capability to exploit underlying correlation within the data. However, the training process of RNN is always time-consuming and inherently difficult though with high performance computing devices like field programmable gate arrays (FPGAs) and graphics processing units (GPUs), which may hinder its application in on site use.

Reservoir computing (RC) is a novel computational framework derived from RNN. RC consists of three layers, named as input, reservoir, and output. Different from RNN, for RC, only the readout coefficients of the output

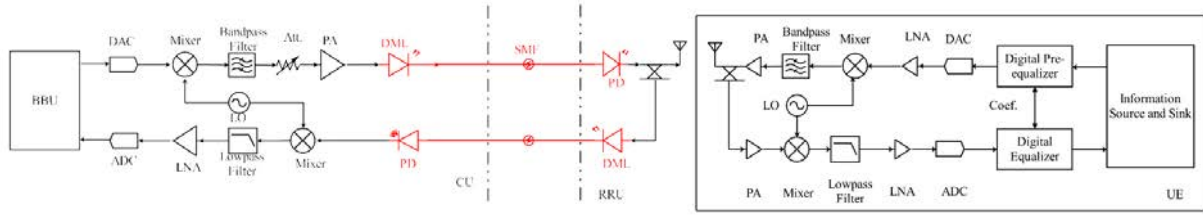


Figure 1. The architecture of RoF system

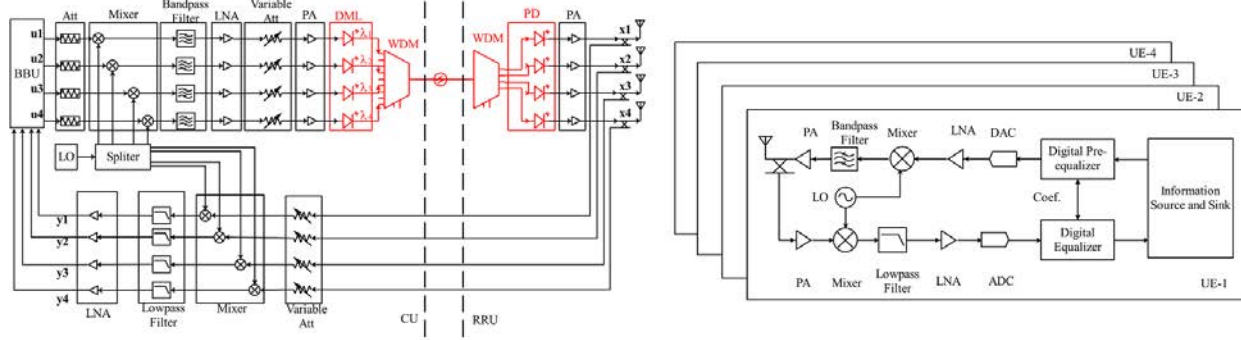


Figure 2. The architecture of WDM-RoF system

layers have to be trained and optimized, while the input and reservoir layers are fixed, and usually random. In this way, the training process has been greatly simplified. With conceptual simplicity and computation cheapness, RC has yielded excellent performance in many benchmark tasks, such as speech recognition [13], nonlinear channel equalization [14], robot control [15], etc. In this paper, RC is applied in the RoF/WDM-RoF system to achieve channel equalization. The simulation results suggest that, in conventional RoF system, the ACPR value of the received signal can be improved about 9 dB by means of RC equalization with 200 reservoir nodes. Then in WDM-RoF system, RC with 500 nodes can provide 6~9 dB gains. More importantly, the gain has roughly positive correlation with the scale of reservoir nodes within certain range. Thus we can further improve the performance by simply increasing the reservoir size.

The remaining paper is organized as follows. In Section II, the architecture of the RoF/WDM-RoF systems are described along with the nonlinear distortion phenomenon. In Section III, the reservoir computing concept and the architecture design for channel equalization are presented and discussed. The evaluation criteria are also given in this section. The verification platform and simulation results are shown in section IV. Eventually, some conclusions remarks and prospects are presented.

II. RoF/WDM-RoF DESCRIPTION

The architecture of the RoF and WDM-RoF systems are depicted in Figure 1 and Figure 2, respectively. The architectures of the RoF/WDM-RoF systems can be roughly

divided into the CU, the RRU and the user equipment (UE). The equalization and pre-equalization are operated at UE. There are two kinds of E/O converters, which are the directly modulated laser (DML) and the Mach-Zehnder modulator(MZM). Compared with the MZM, DML exhibits advantages on cost efficiency, size and power consumption. Hence, we use the DML in the RoF/WDM-RoF system. However, the DML also suffers from the frequency chirp and nonlinear distortion, which can be described by following set of equations:

$$P(t) = P_0[1 + I(t)] \quad (1)$$

$$\frac{d\phi(t)}{dt} = \frac{\beta_c}{2} \left[\frac{1}{P(t)} \frac{dP(t)}{dt} + \kappa P(t) \right] \quad (2)$$

$$\Delta\nu(t) = \frac{1}{2\pi} \frac{d\phi(t)}{dt} \quad (3)$$

$$E(t) = \sqrt{1 + I(t)} \exp[-j\phi(t)] \quad (4)$$

where $P(t)$ is the DML's output power, $I(t)$ is the modulation current, β_c is the linewidth enhancement factor, κ is the structure dependent parameter related to the optical gain compression, $\phi(t)$ is the optical signal phase, $\Delta\nu(t)$ is the frequency chirp and $E(t)$ is the envelop of the normalized optical field.

Besides the impairments mentioned above, other nonlinear distortions happen when the optical signals traveling through the fiber due to Kerr effect and inelastic scattering. In the RoF system, the spectrum broadening of the transmitting signal is caused by the self-phase modulation (SPM). In WDM-RoF system, further nonlinear distortion exist, which includes cross-phase modulation (XPM), four wave mixing (FWM), stimulated Brillouin scattering, etc.

So far, there already existed several techniques can individually deal with those nonlinear distortion. However, since RoF/WDM-RoF system is a complicated integrated electrical-optical system, overall linearization technique is necessary.

III. RERESERVOIR COMPUTING AND PROPOSED EQUALIZATION METHODS

RC is a new paradigm of the RNN. It can be considered as a nonlinear high-dimensional mapping from the input signal to the reservoir state. Meanwhile, the reservoir serves as a memory, providing the temporal context, which is a crucial reason for using the RNN. A variety of RC methods have been reported in the literatures, such as echo state network (ESN) [14], liquid state machine (LSM) [16], backpropagation-decorrelation learning [17], and delay line feed-back [18]. Among these methods, ESN has been widely used for its simplicity and scalability.

A. Echo State Network

For a given input signal $u(n) \in \mathbb{R}^{N_u}$, a desired target output signal $u_{\text{target}}(n) \in \mathbb{R}^{N_y}$ is known. Here, $n = 1, 2, \dots, T$ is the discrete time and T is the number of data points in the training dataset. For prediction tasks, the objective is to learn a model to make the output $y(n)$ of the model match $y_{\text{target}}(n)$ as well as possible, and more importantly, generalizes well to the test dataset. Normalised-Mean-Square Error (NMSE) is always used as the evaluation index

$$\text{NMSE}(y, y_{\text{target}}) = \frac{1}{N_y} \sum_{i=1}^{N_y} \frac{\sum_{n=1}^T |y - y_{\text{target}}|^2}{\sum_{n=1}^T |y_{\text{target}}|^2} \quad (5)$$

The typical update equation of ESN is

$$x(n+1) = (1 - \alpha)x(n) + \alpha f[W_{\text{in}}[1; u(n+1)] + Wx(n)] \quad (6)$$

where $x(n) \in \mathbb{R}^N$ is a vector which indicates the reservoir state, f is the nonlinear function that is applied element-wise, $[\cdot; \cdot]$ stands for vectorial (matrix) concatenation, $W_{\text{in}} \in \mathbb{R}^{N \times (1+N_u)}$ and $W \in \mathbb{R}^{N \times N}$ are the input and recurrent weight matrices respectively, $\alpha \in (0, 1]$ is the leaking rate, N is the number of reservoir nodes. W_{in} is used to map the input to the reservoir space.

The linear readout layer is defined as

$$y(n) = W_{\text{out}}[1; u(n); x(n)] \quad (7)$$

where $y(n) \in \mathbb{R}^{N_y}$ is the network output, $W_{\text{out}} \in \mathbb{R}^{N_y \times (1+N_u+N)}$ is the output weight matrix, and $[\cdot; \cdot; \cdot]$ stands for a vectorial (matrix) concatenation. In the train phase, W_{in} , W , α are generated randomly. W_{in} , W are fixed random matrix. Initial $x(0)$ is set to zeros. Then the reservoir state is collected step

by step according to Equation (6). Finally, the ridge regression is used to minimize NMSE, thus obtaining the output weight matrix W_{out}

$$W_{\text{out}} = Y_{\text{target}} X^T (X X^T + \lambda I)^{-1} \quad (8)$$

where $Y_{\text{target}} \in \mathbb{R}^{N_y \times T}$ is concatenated by all Y_{target} corresponding to the $u(n)$, $X \in \mathbb{R}^{(1+N_u+N) \times T}$ is concatenated by all $[1; u(n); x(n)]$ produced by injecting $u(n)$ to the reservoir, I is the identity matrix, and λ is the regularization coefficient which is always used to avoid over-fitting.

In the prediction phase, $u(T+i)$ ($i = 1, 2, 3, \dots$) is injected into Equation (6) to get the corresponding reservoir state stepwise, then Equation (7) is used to obtain the corresponding output $y(T+i)$.

B. Equalization in WDM-RoF system

In the WDM-RoF system, the transmitting signal abbreviated as TR is a matrix $\in \mathbb{C}^{4 \times 25000}$. Each row of the matrix represents one complex signal carried by a subcarrier. The receiving signal abbreviated as RE also is a matrix $\in \mathbb{C}^{4 \times 25000}$ after the noisy channel transmission, while each row of the matrix represents one complex signal that match the corresponding transmitting signal. Herein, RC works as a black-box to compensate the signal distortion resulting from nonlinearity of single wavelength and the interference between multiple wavelengths. The distorted signals RE are injected to the RC, while the corresponding transmitting signal serve as the target matrix. As a pre-processing, each row of TR, namely $\text{TR}(i, :)$ ($i = 1, 2, 3, 4$) is normalised by the maximum value of absolute value in this row. Meanwhile, each row of RE, namely $\text{RE}(i, :)$ is also normalised by the maximum value of the absolute value in this row. Both the normalized $\text{TR}(i, :)$ and $\text{RE}(i, :)$ are complex row vector, but for RC, it can only handle the real number, so each of them is divided into a column vector, thus obtaining $[\text{real}(\text{TR}(i, :)); \text{imag}(\text{TR}(i, :))]$, $[\text{real}(\text{RE}(i, :)); \text{imag}(\text{RE}(i, :))]$, where $\text{real}()$ means taking the real part of the complex number elementwise and $\text{imag}()$ means taking the imaginary part of the complex number elementwise. Thus the input dimension N_u and output dimension N_y equal to 8.

In the train phase, $\text{RE}(:, j)$ which is a 8×1 vector ($j = 1, 2, \dots, 12500$) is injected to Equation (6) to obtain the corresponding reservoir state $x(j)$ stepwise, then Equation (8) is used to calculate the output matrix W_{out} , to minimize the NMSE of the network output $Y (\in \mathbb{R}^{8 \times 12500})$ with the transmitting signal $\text{TR}(:, j)$ ($j = 1, 2, \dots, 12500$). As a preliminary verification, in the prediction phase, all the receiving $\text{RE}(:, j)$ ($j = 1, 2, \dots, 25000$) is injected to the reservoir by using Equation (6) and collect the corresponding reservoir state $x(j)$. After that, Equation (7) is used to calculate the network output which is equivalent to the signal after equalization.

Referring to [19], the input scaling of W_{in} , spectral radius of W , and leaking rate α are three main hyper parameters to

optimize the performance of the RC, thus these parameters are finely tuned in the train process of RC by using the grid search. Finally, these parameters are all set to 0.5. The regularization coefficient is set to 0.001.

C. Performance Evaluation

The NMSE, ACPR are used to evaluate the equalization performance of the RC. Let $X_p(f)$ be the power spectral density of the signal X_p at the p_{th} UE, where $p \in [1, 2, 3, 4]$. Then the ACPR of signal $X_p(f)$ is defined as

$$ACPR_p(\text{dB}) = 10\log_{10} \left[\frac{\int_{\text{adjband}} X_p(f) df}{\int_{\text{mainband}} X_p(f) df} \right] \quad (9)$$

and the NMSE of signal X_p is defined as

$$NMSE_p(\text{dB}) = 10\log_{10} \left[\frac{\sum_{n=1}^L |u_p(n) - \hat{u}_p(n)|^2}{\sum_{n=1}^L |u_p(n)|^2} \right] \quad (10)$$

where $u_p(n)$ is the transmitting value of p_{th} signal at time n , $\hat{u}_p(n)$ is the predicted transmitting value of p_{th} signal at time n .

IV. VERIFICATION PLATFORM AND SIMULATION RESULTS

A. Verification Platform

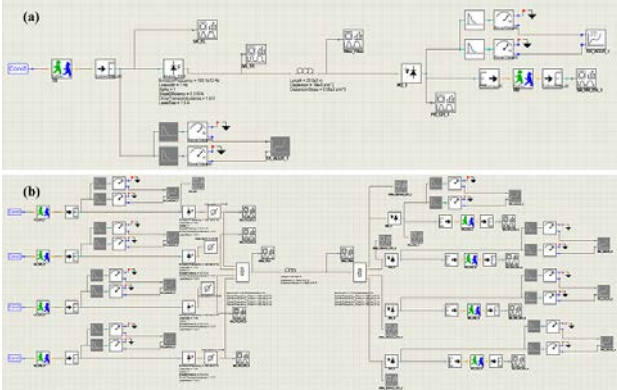


Figure 3. The schemes of the verification system.(a) RoF system.(b) WDM-RoF system.

In order to demonstrate our proposed algorithm, two verification platforms are developed, which are depicted by Figure 3 (a) and (b). Both of them are based on the VPI photonics design suite and Octave software. The transmitting orthogonal frequency division multiplexing (OFDM) signals, whose centre frequency is 3.5 GHz with 200 MHz bandwidth are generated by using Octave at PC. The RC equalization also performed in Octave platform. The signal distortion caused by the optical components such as DML, fiber, and PD are simulated by the VPI. Through the co-simulation interface, the RF signals are loaded and saved by the VPI. The key parameters of the VPI verification platforms are listed in Table 1.

TABLE 1. THE KEY PARAMETERS OF RoF/ WDM-RoF SYSTEM

	Parameter	Value
General	Number of Path	1 or 4
	Length of Frame	25000(Symbols)
	Sample Rate	20 GSa/s
DML	RIN	-150 dB/Hz
	Linewidth	400 kHz
	Chirp Factor	10 GHz/W
	Optical Carrier	1551.2~1553.6 nm
	Laser Bias	1.5 A
	Slope Efficiency	0.3W/A
	Average Power	10 mW
PD(PIN)	Responsivity	0.7 A/W
	Dark Current	100 nA
	Thermal Noise	$20e^{-12}$ A/Hz ^{1/2}
	Shot Noise	On
Fiber	Length	20 km
	Attenuation	0.2 dB/km
	Dispersion	$16e^{-6}$ s/m ²
	Dispersion Slop	80 s/m ³
	Nonlinear Index	$2.6e^{-20}$ m ² /w
WDM	Bandwidth	35 GHz
	Optical Filter Space	0.1 THz

B. Simulation Results and Discussion

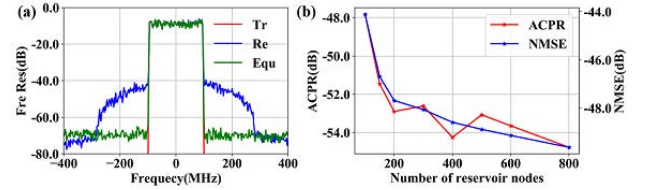


Figure 4. (a) The frequency response of the transmitting signal, the receiving signal, and the signal after the equalization. Tr, Re, Equ indicate the transmitting signal, the receiving signal, the signal after the equalization by using reservoir computing with 200 reservoir nodes, respectively. (b) The relationship between the ACPR/NMSE and the reservoir size.

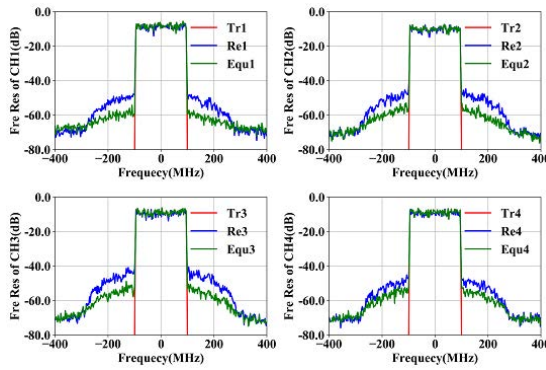
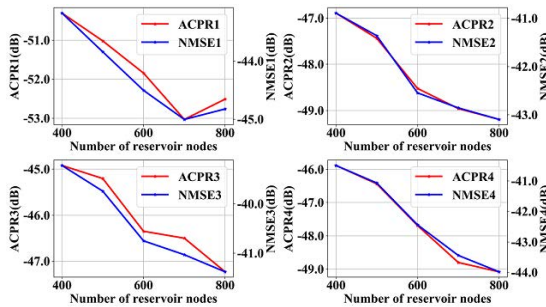
For the RoF system described in Figure 3(a) and Table 1, the reservoir computing with 200 nodes is used to perform the equalization, whose result is shown in Figure 4(a). The equalization process is similar with the WDM-RoF system which is described in detail in Section III B. The ACPR and NMSE value of the receiving signal before the equalization is -33.621 dB and -7.3127 dB, respectively. After equalization, the ACPR and NMSE decreases to -42.898 dB and -47.682 dB, obtaining 9.277 dB gain and 40.377 dB gain separately. Besides the three parameters mentioned in Section III, the number of the reservoir nodes also play an important role in the performance of RC. Herein, we investigate the performance of the equalization on the number of the reservoir nodes while keeping other hyper parameters fixed. The results are presented in Figure 4(b) and Table 2. We can see that by simple increasing the reservoir size, the ACPR/NMSE gain performance can be adjusted easily.

TABLE 2. THE VALUES OF ACPR/NMSE OF EACH CHANNEL BEFORE AND AFTER EQUALIZATION FOR RoF SYSTEM

	RC100	RC150	RC200	RC300	RC400	RC500	RC600	RC800
ACPR(dB)	-47.830	-51.461	-52.898	-52.613	-54.252	-53.071	-53.647	-54.770
NMSE(dB)	-44.109	-46.690	-47.682	-48.059	-48.585	-48.878	-49.130	-49.624

TABLE 3. THE VALUES OF ACPR/NMSE OF EACH CHANNEL BEFORE AND AFTER EQUALIZATION FOR WDM-RoF SYSTEM

		Tr	Re	RC400	RC500	RC600	RC700	RC800
ACPR(dB)	CH-1	-180.68	-41.718	-50.308	-51.020	-51.844	-53.029	-52.509
	CH-2	-175.36	-38.475	-46.889	-47.435	-48.523	-48.960	-49.195
	CH-3	-178.09	-35.749	-44.918	-45.202	-46.350	-46.501	-47.233
	CH-4	-174.80	-40.311	-45.886	-46.438	-47.693	-48.803	-49.084
NMSE(dB)	CH-1		-5.6670	-43.175	-43.841	-44.503	-45.002	-44.822
	CH-2		-8.1808	-40.892	-41.361	-42.545	-42.856	-43.095
	CH-3		-0.2934	-39.224	-39.744	-40.750	-41.031	-41.377
	CH-4		3.4213	-40.488	-41.064	-42.439	-43.444	-43.983

**Figure 5.** The frequency response of the transmitting signals, the receiving signals, and the signals after the equalization. Tr, Re, Equ indicate the transmitting signal, the receiving signal, the signal after equalization, respectively. CH means channel.**Figure 6.** The ACPR/ NMSE of each channel after equalization with different number of reservoir nodes.

Furthermore, for the WDM-RoF system described in Figure 3(b) and Table 1, the frequency response of the signal is shown in Figure 5. Obviously, after the equalization by RC with 500 reservoir nodes, the frequency response for each signal is improved significantly. For subcarrier 1 to 4, the ACPR gains are 9.3019 dB, 8.9603 dB, 9.4533 dB, 6.1272 dB, respectively. We also study the influence that reservoir size makes on the

equalization performance. Simulation results are shown in Table 3 and Figure 6. From Figure 6, we can see the ACPR has roughly positive relationship with NMSE. When ranging from 400 to 700, ACPR/NMSE of each channel is positively related with the reservoir size.

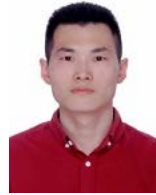
V. CONCLUSIONS

In this paper, a novel equalization method based on the reservoir computing is introduced in the RoF/WDM-RoF system, where RC works as a black box. Its nonlinear mapping capability from the lower space to the higher space and the dynamic memory ability make it powerful to compensate the distortion caused by the optical components. Its simple architecture, low computing resource consumption and high speed enable it to be a competitive candidate for signal equalization. When the number of the reservoir is set to 500, 9.3019 dB, 8.9603 dB, 9.4533 dB, and 6.1272 dB ACPR gain are obtained for channel 1-4, respectively. Besides, the ACPR gain can be improved by simply increasing the size of the reservoir. For on-site use, more details should be considered, such as the power consumption, the hardware resource consumption, and the speed restrictions. To solve this potential issues, new topological structure [20] and the way of hardware implementation such as the optical computing of reservoir computing [21] should be taken into consideration.

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