

# NONLINEAR CHANNEL EQUALIZATION AND ADAPTIVE LEARNING METHODS FOR LOW-POWER VLC SYSTEMS

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**Abstract:** To address the challenges of limited modulation bandwidth and nonlinear channel impairments in low-power visible light communication (VLC) systems, this paper proposes a hardware-software co-designed adaptive learning equalization scheme. At the physical layer, a hardware pre-equalization circuit is designed to compensate for Light Emitting Diode (LED) high-frequency attenuation, thereby expanding the system's physical bandwidth. At the algorithmic layer, an adaptive gradient descent learning algorithm arctan-softsign variable-step least mean square (A-SVSLMS) based on the softsign activation function is proposed. This algorithm leverages the nonlinear mapping mechanism between the step size factor and the error gradient to achieve dynamic optimization of weight updates, effectively resolving the challenge faced by traditional algorithms in balancing convergence speed and steady-state accuracy. Experimental results demonstrate that under a 0.06 W light source, the system's -3 dB bandwidth increases from 1.6 MHz to 13.5 MHz. Compared to traditional LMS algorithms, the proposed algorithm exhibits faster learning rates and enhanced robustness, successfully achieving 2 Mbps error-free transmission at a 0.55 m distance. This validates the application potential of lightweight intelligent algorithms in resource-constrained devices.

**Keywords:** Visible light communication; Channel equalization; Adaptive learning algorithm; Softsign function

## 1 INTRODUCTION

With the evolution of sixth-generation mobile communications and Internet of Things (IoT) technologies, visible light communication (VLC) has emerged as a key solution for indoor access due to its abundant spectrum resources, resistance to electromagnetic interference, and eco-friendly low-power advantages. However, in practical low-power applications such as smart homes and sensor networks, cost and energy efficiency constraints often limit signal sources to commercial Light Emitting Diode (LED) operating at the microwatt level. The inherently high junction capacitance of such devices results in extremely narrow modulation bandwidth, causing severe Inter Symbol Interference (ISI). Simultaneously, the extremely low transmission power degrades the signal-to-noise ratio (SNR) at the receiver, leading to strong nonlinearity and random time-varying characteristics in the channel.

To overcome these physical limitations, existing research primarily focuses on hardware compensation and algorithmic equalization. While hardware pre-equalization techniques can expand bandwidth through analog filtering, purely hardware-based approaches struggle to dynamically adapt to random channel fluctuations. At the signal processing level, computational intelligence techniques have been widely introduced to counter nonlinear distortions. Equalizers based on deep neural networks (DNNs) offer high accuracy but suffer from massive parameter scales and computational overhead, making them unsuitable for resource-constrained IoT terminals. Traditional least mean square (LMS) algorithms feature low computational complexity, yet their fixed-step mechanism faces trade-offs between convergence speed and steady-state accuracy, hindering effective tracking of nonlinear channels in low-light environments.

In response, this paper proposes a hardware-software co-optimized intelligent equalization scheme for low-power VLC systems. Key contributions include:

(1) Hardware pre-equalization circuit design: addressing bandwidth constraints, an active feedback-based high-pass filter circuit compensates high-frequency attenuation, successfully expanding the system -3 dB bandwidth from 1.6 MHz to 13.5 MHz.

(2) Softsign-based adaptive learning algorithm arctan-softsign variable-step least mean square (A-SVSLMS): To achieve intelligent tracking with low computational overhead, this paper proposes an improved gradient descent algorithm. Utilizing the softsign activation function, this algorithm constructs a nonlinear mapping mechanism between the step factor and error, enabling dynamic optimization of weight updates.

## 2 RELATED WORK

Enhancing the transmission performance of VLC systems primarily involves two dimensions: hardware bandwidth expansion and digital algorithm equalization.

In their review on 6G VLC technology, Chi N et al. profoundly pointed out that the large junction capacitance of commercial light-emitting diodes severely limits their modulation bandwidth, constituting a core obstacle restricting system communication rates. Simultaneously, complex channel environments pose significant challenges to signal integrity [1]. To overcome this physical limitation, the academic community initially focused on hardware pre-equalization techniques at the transmitter end, aiming to compensate for high-frequency signal attenuation through

circuit design. Bostanoglu M et al. established comprehensive channel and device models for full-featured VLC systems, designing an efficient pre-equalizer based on these models. Experiments demonstrated that this approach significantly enhances the system's modulation bandwidth and transmission stability under real-world operating conditions [2]. To pursue even higher transmission rates, Zhang R et al. proposed a low-complexity pre-equalizer circuit design. By optimizing the analog circuit structure, this approach successfully supported VLC system bandwidths up to 1.5 GHz. It maintained low hardware implementation costs while significantly expanding VLC's application potential in high-frequency bands [3]. Subsequently, Ramadhan M A et al. delved into the specific engineering implementation challenges of pre-equalizers. Within an intelligent signal processing framework, they designed and implemented dedicated pre-equalization hardware for visible light communication. Their work validated the effectiveness of precise frequency-domain compensation in eliminating intersymbol interference (ISI), providing valuable experimental data support for subsequent hardware optimization [4].

Although simple hardware circuits can effectively expand bandwidth, their performance is often constrained by the degree of matching between model accuracy and system dynamic characteristics. Kisacik R et al. found that the traditional first-order low-pass LED model exhibits significant errors when describing high-frequency responses. Consequently, they proposed a novel LED response model and applied it to the parameter design of pre-equalizers. This approach significantly improved the equalizer's fitting accuracy to the actual physical characteristics of LEDs, thereby achieving superior signal recovery performance [5]. Building upon this, to address more complex channel environments and enable real-time processing, Khawatmi A et al. recently proposed a hybrid equalization scheme combining hardware and software. This approach employs a hardware pre-equalizer at the transmitter for coarse compensation, combined with an LMS adaptive post-equalization algorithm at the receiver for fine-tuning. It successfully achieved a real-time transmission rate of 500 Mb/s over a single channel, demonstrating the advantages of the "pre-equalization + post-equalization" cooperative architecture in mitigating residual ISI [6]. As VLC systems evolve toward multi-input multi-output (MIMO) and higher-order modulation schemes, the application scenarios for equalization techniques become increasingly complex. Galvao L G et al. investigated equalization strategies for bandwidth-constrained VLC systems under MIMO architectures, specifically focusing on multi-band carrier-free amplitude-phase modulation (m-CAP). By deploying specialized equalization algorithms at the receiver, they effectively suppressed crosstalk between MIMO channels and signal distortion caused by higher-order modulation, offering new insights for enhancing system spectral efficiency [7].

However, as communication rates continue to increase, nonlinear distortion in LEDs and nonlinear channel impairments have gradually become the dominant factors limiting system performance, rendering traditional linear equalization techniques inadequate. Miao P et al. introduced deep learning techniques, leveraging the powerful nonlinear fitting capabilities of deep neural networks to address complex impairments in indoor VLC channels. Experiments demonstrated that deep learning-based equalizers significantly outperform traditional methods in reducing bit error rates (BER), particularly excelling in handling nonlinear distortion [8]. Concurrently, researchers have begun re-examining the potential impact of pre-equalization techniques on SNR. Zhou Z et al. conducted an in-depth analysis of the impact of analog and digital pre-emphasis techniques on the SNR of bandwidth-constrained optical transceivers. They pointed out that while pre-emphasis enhances high-frequency components, it may also amplify high-frequency noise. Therefore, an optimal balance must be found between bandwidth expansion and SNR degradation. This theoretical analysis provides important guiding principles for selecting equalization strategies [9]. To balance computational complexity and nonlinear compensation performance, Tian D et al. proposed a Volterra series-assisted neural network equalizer. This approach combines the strengths of Volterra series in handling nonlinear memory effects with the feature extraction capabilities of neural networks, constructing an efficient composite equalization structure. It effectively compensates for channel impairments in VLC systems while avoiding the excessive computational overhead associated with using deep neural networks alone [10].

In summary, existing single approaches struggle to simultaneously satisfy the multiple constraints of low power consumption, low complexity, and high robustness. Therefore, this paper proposes a hardware-software co-optimization scheme. Building upon hardware circuitry to overcome physical bandwidth limitations, it introduces a softsign function to enhance the LMS step size mechanism. This aims to achieve intelligent adaptive tracking of nonlinear channels at an extremely low computational cost.

### 3 SYSTEM DESIGN AND ALGORITHM RESEARCH

Addressing the challenges of bandwidth limitations and severe nonlinear distortion in low-power LEDs, a single approach struggles to balance both speed and reliability. In light of this, this chapter proposes a hardware-software co-optimization strategy. First, an active feedback pre-equalization circuit is designed to expand the physical bandwidth through hardware circuit design. Second, an adaptive learning algorithm A-SVSLMS based on the softsign function is introduced, leveraging intelligent gradient optimization to enhance the system's decision accuracy and robustness.

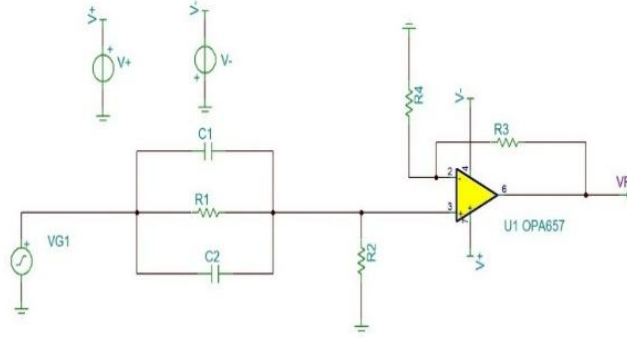
#### 3.1 Hardware Circuit Design

This paper designs an active equalization circuit. The equalizer features high-frequency amplification to compensate for high-frequency components, thereby extending the -3 dB bandwidth of the LED. The pre-equalization circuit for visible light communication designed in this paper is shown in Figure 1. The circuit incorporates an RC passive high-pass

filter, constructed by connecting capacitor  $C_1$  and resistor  $R_1$  in parallel, then in series with load resistor  $R_2$ . The amplification stage employs a low-distortion voltage-feedback operational amplifier (OPA657) to form a voltage-series feedback circuit. The signal enters the amplifier through the non-inverting input, preserving the input signal's phase. The OPA657 achieves a gain-bandwidth product of 1.6 GHz, amplifying the effective signal and enhancing the LED's modulation index.

The ratio of the output to the input of the above circuit yields the frequency response of the equalization circuit as given by Equation 1.

$$H(j\omega) = \frac{V_o}{V_i} = \left(1 + \frac{R_3}{R_4}\right) \cdot \frac{R_2}{R_1 + R_2} \cdot \frac{1 + j\omega / \omega_z}{1 + j\omega / \omega_p} \quad (1)$$



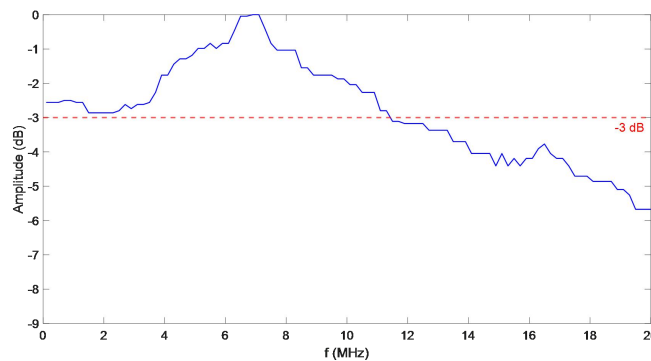
**Figure 1** Schematic Diagram of RC Equalization Circuit

Among them,  $C = C_1 + C_2$ ,  $\omega_z = \frac{1}{R_1 C_1}$ ,  $\omega_p = \frac{R_1 + R_2}{R_1 R_2 C}$ .

The amplitude response of the pre-emphasis circuit can be theoretically calculated using Equation 1. The equation for the -3dB cutoff frequency is given by Equation 2.

$$\omega_{-3dB} = \omega_z \omega_p \sqrt{\frac{1}{1 / (\omega_p^2 - 2\omega_z^2)}} \quad (2)$$

The transmitted signal is processed using the aforementioned equalization circuit, and the LED operates within its linear region via a bias circuit. By measuring the LED's output amplitude at each frequency point, the frequency response is obtained as shown in Figure 2. As shown in Figure 2, the frequency response of the equalized LED exhibits an initial rise followed by a decrease. Using the maximum amplitude of the received signal frequency as the reference, the LED's -3 dB bandwidth is determined to be 13.5 MHz. The introduction of the equalization circuit significantly broadens the LED's effective modulation bandwidth, providing a solid foundation for achieving higher data rates and enhanced reliability in VLC systems under low-light conditions.



**Figure 2** Amplitude Frequency Response Curve of LED after Equalization

### 3.2 Algorithm Research

Although hardware equalization technology can broaden system bandwidth, inter-symbol interference arising from imperfect channel characteristics remains the primary factor limiting communication rates and increasing BER in low-power LED-based VLC systems. Single hardware compensation struggles to maintain stable decision performance. Therefore, to enhance system performance, adopting adaptive equalization techniques based on computational intelligence at the receiver is indispensable. By dynamically adjusting weighting coefficients, these equalization techniques can effectively mitigate signal distortion caused by imperfect channel characteristics.

The adaptive equalization algorithm dynamically adjusts the tap coefficients of the equalizer based on channel characteristics. The filter update equation in this algorithm is given by Equation 3.

$$w(n+1) = w(n) - \frac{1}{2} \mu \nabla J(n) \quad (3)$$

where  $w$  is the withdrawal coefficient,  $n$  is the iteration count, and  $\nabla J(n)$  is the unbiased gradient vector.

Assuming the output of the filter at time  $n$  is  $\hat{d}(n)$ , and the desired signal at that time is  $d(n)$ , then the error signal  $e(n)$  can be expressed as Equation 4.

$$e(n) = d(n) - \hat{d}(n) \quad (4)$$

The cost function  $J(n)$  can be expressed as Equation 5

$$J(n) = E[e^2(n)] \quad (5)$$

The partial derivative of the cost function with respect to  $w(n)$  can be expressed as Equation 6

$$\nabla J(n) = \frac{\partial J(n)}{\partial w(n)} = -2e(n) \frac{\partial e(n)}{\partial w(n)} = -2e(n)x(n) \quad (6)$$

Among them  $x(n)$  is the input signal for the transmitter.

Therefore, the updated equation for the new filter coefficients is given by Equation 7.

$$w(n+1) = w(n) + \mu e(n)x(n) \quad (7)$$

When the step size  $\mu$  is large, the filter weight adjustment rate is fast, enabling rapid algorithm convergence but potentially leading to significant steady-state error or even divergence. When the step size is small, the algorithm converges more slowly but exhibits minimal steady-state error and greater system stability.

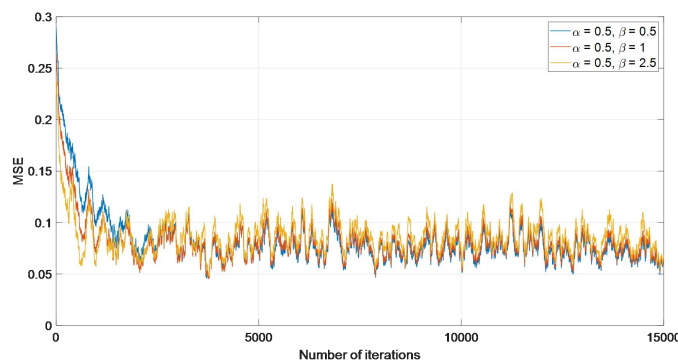
Since the convergence speed and steady-state error of the LMS algorithm are closely related to the step size factor, a fixed step size factor struggles to balance both aspects. Therefore, variable-step-size LMS algorithms were proposed. This paper employs the softsign function to adjust the step size and error according to Equation 8.

$$\mu = \frac{|e(n)|}{(1 + |e(n)|)} \quad (8)$$

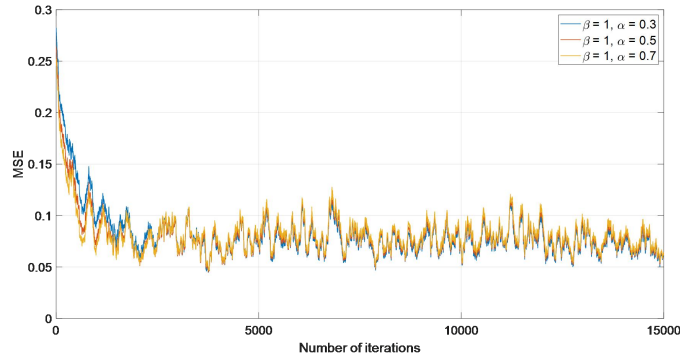
The softsign function lacks exponential operations, resulting in significantly lower computational complexity compared to the Sigmoid function, making it highly hardware-friendly for implementation. The A-SVSLMS proposed in this paper introduces nonlinear compression via the inverse tangent function, thereby establishing the relationship between the step size  $\mu$  and the convergence error  $e(n)$ . The A-SVSLMS equalization algorithm limits the step size during large convergence errors while finely adjusting the step size during small convergence errors. This achieves a balance between convergence speed and steady-state error, stabilizing the steady-state error after convergence. The specific form of the function is given by Equation 9.

$$\mu = \frac{\alpha * |e(n)| * \arctan(|e(n)|^\beta)}{(1 + |e(n)|)} \quad (9)$$

To obtain suitable parameters, we analyzed the convergence characteristics and mean squared error performance of the algorithm under different parameter settings. Simulation results for varying values of  $\alpha$  and  $\beta$  are shown in Figures 3 and 4.



**Figure 3** Convergence Curves of A-SVSLMS Algorithm under Different  $\beta$  Conditions

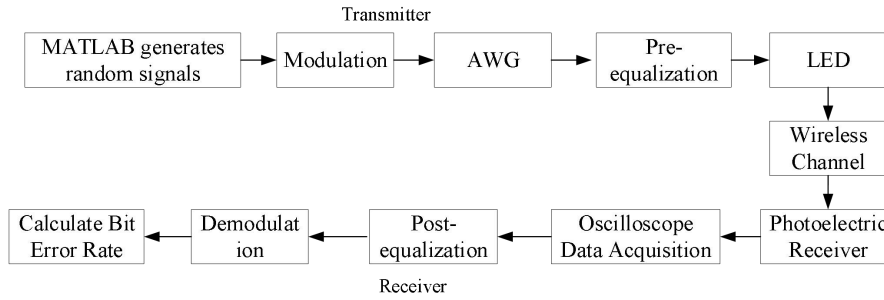


**Figure 4** Convergence Curves of A-SVSLMS Algorithm under Different  $\alpha$  Conditions

As shown in Figure 3, when  $\alpha = 0.5$ , for different values of  $\beta$ , the convergence speed increases as the value of  $\beta$  decreases. This is due to larger step sizes during convergence. When  $\beta$  is set to 0.5 and 1, the convergence speeds of the algorithms are similar. As shown in Figure 4, when  $\beta = 1$ , with different values of  $\alpha$ , the larger the value of  $\alpha$ , the larger the step size becomes. While accelerating the convergence speed, it also increases the mean squared error. Therefore, in this channel environment, setting  $\alpha$  to 0.5 and  $\beta$  to 1 achieves a balance between algorithm convergence speed and steady-state error. The algorithm converges after 700 iterations.

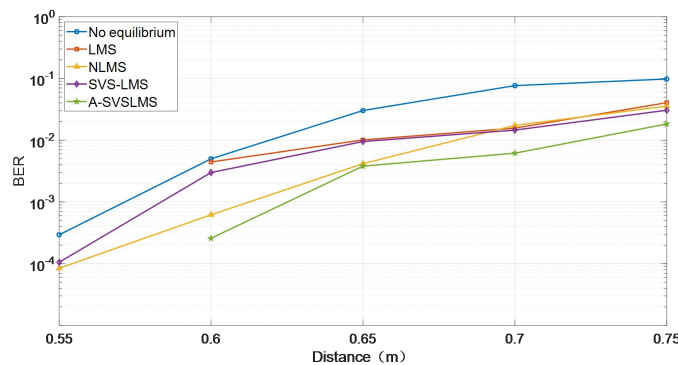
#### 4 SYSTEM SETUP AND EXPERIMENTAL ANALYSIS

The VLC system block diagram constructed in this paper is shown in Figure 5.



**Figure 5** Experimental System Block Diagram

The experimental procedure and parameter settings are as follows: First, a pseudorandom sequence On-Off Keying (OOK) baseband signal is generated using MATLAB. The signal generator is controlled via SCPI commands to drive the pre-equalized LED transmitter. At the receiver, a photodetector and oscilloscope are used to capture the signal, and MATLAB is employed for equalization, demodulation, and BER calculation. To validate the performance of the proposed algorithm, this study compares the LMS algorithm, normalized least mean squares (NLMS) algorithm, sigmoid variable step least mean squares (SVSLMS) algorithm, and the proposed A-SVSLMS algorithm at different distances. The system BER performance comparison results are shown in Figure 6.

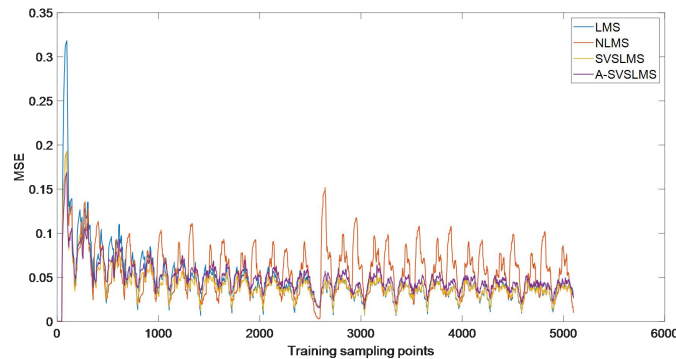


**Figure 6** Comparison of BER at Different Distances

As shown in Figure 6, the error rate performance of the equalized system consistently outperforms that of the unequaled system. At a distance of 0.55 m, after processing with both the LMS equalization algorithm and the A-SVSLMS equalization algorithm, the system error rate reaches zero, achieving error-free transmission at this distance.

However, since the LMS algorithm employs a fixed step size that cannot be adjusted based on the convergence error, its adaptability to the system is relatively poor. At a communication distance of 0.75 m, the pre-equalization system's BER is  $9.8 \times 10^{-2}$ . After processing with the A-SVSLMS equalization algorithm, the system's BER decreases to  $1.8 \times 10^{-2}$ . The error rate has been reduced to 18% of the original value.

This paper evaluates the convergence curves of different equalization methods at a communication distance of 0.75 m, as shown in Figure 7.



**Figure 7** Convergence Curves of Different Equalization Algorithms at 0.75 m

Based on the performance of several equalization algorithms shown in Figure 7, it can be observed that the LMS algorithm exhibits the slowest convergence rate. Although the NLMS algorithm achieves improved convergence speed, it results in a larger steady-state error after convergence. In contrast, both the SVSLMS and A-SVSLMS equalization algorithms demonstrate faster convergence characteristics. The A-SVSLMS algorithm proposed in this paper exhibits the most stable mean square error (MSE) after convergence. This stability arises from the smaller step sizes adopted in the later stages of the algorithm, which effectively reduce the MSE. Overall, as distance increases, the optical signal at the receiver weakens, leading to a continuous rise in the system BER. Compared to other equalization algorithms, the A-SVSLMS equalization algorithm delivers the optimal BER performance, significantly enhancing the system's interference resistance under low-light conditions.

## 5 CONCLUSIONS

To address the challenges of limited modulation bandwidth and nonlinear distortion in low-power VLC systems, this paper proposes a hardware-software co-optimized intelligent equalization scheme. At the hardware level, an active pre-equalization drive circuit is designed to compensate for LED high-frequency attenuation, successfully expanding the system's -3 dB bandwidth from 1.6 MHz to 13.5 MHz and effectively overcoming the physical limitations of the components. At the algorithmic level, an A-SVSLMS adaptive equalization algorithm based on nonlinear mapping is introduced. This resolves the trade-off between convergence speed and steady-state accuracy inherent in traditional fixed-step algorithms, significantly enhancing signal decision robustness in low-light environments. Experimental results demonstrate that the system achieves error-free transmission of 2 Mbps data over a 0.55 m distance under a 0.06 W weak light source, validating the effectiveness of the proposed design and algorithm for low-power communication.

## COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

## REFERENCES

- [1] Chi N, Zhou Y, Wei Y, et al. Visible light communication in 6G: Advances, challenges, and prospects. *IEEE Vehicular Technology Magazine*, 2020, 15(4): 93-102.
- [2] Bostanoglu M, Dalveren Y, Catak F O, et al. Modelling and design of pre-equalizers for a fully operational visible light communication system. *Sensors*, 2023, 23(12): 5584.
- [3] Zhang R, Xiong J, Li M, et al. Design and implementation of low-complexity pre-equalizer for 1.5 GHz VLC system. *IEEE Photonics Journal*, 2024, 16(1): 1-10.
- [4] Ramadhan M A, Tanudjaja G H, Setiawan E, et al. Design and implementation of a pre-equalizer for visible light communication. *2021 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*. IEEE, 2021: 1-2.
- [5] Kisacik R, Yagan M Y, Uysal M, et al. A new LED response model and its application to pre-equalization in VLC systems. *IEEE Photonics Technology Letters*, 2021, 33(17): 955-958.
- [6] Khawatmi A, Saeed N, Atef M. Real-time single-channel 500 Mb/s visible light communication using pre-equalizer and LMS adaptive post-equalization. *Optics & Laser Technology*, 2025, 192: 114082.

- [7] Galvao L G, Ahmad Z, Rajbhandari S. Study of MIMO m-CAP with equalizer for a band-limited VLC system. 2020 12th International Symposium on Communication Systems, Networks and Digital Signal Processing (CSNDSP). IEEE, 2020: 1-6.
- [8] Miao P, Yin W, Peng H, et al. Study of the performance of deep learning-based channel equalization for indoor visible light communication systems. *Photonics*. MDPI, 2021, 8(10): 453.
- [9] Zhou Z, Odedeyi T, Kelly B, et al. Impact of analog and digital pre-emphasis on the signal-to-noise ratio of bandwidth-limited optical transceivers. *IEEE Photonics Journal*, 2020, 12(2): 1-12.
- [10] Tian D, Miao P, Peng H, et al. Volterra-aided neural network equalization for channel impairment compensation in visible light communication system. *Photonics*. MDPI, 2022, 9(11): 845.