

# Multi-Channel Nonlinearity Mitigation Using Neural-Network-Based Feedback Cancellation with Channel Decision Passing Algorithm

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**Abstract**—This paper investigates neural network (NN) based feedback cancellation in combination with the channel decision passing (CDP) algorithm for the mitigation of multi-channel receiver nonlinearities. The CDP algorithm iteratively assesses output symbols from each channel, utilizing them in successive channels to mitigate nonlinearities within a feedback loop until convergence across all channels is achieved. While prior work relied on a polynomial-based model to estimate the harmonic distortions and intermodulation products introduced by the nonlinearities of the analog front end (AFE), this paper employs trained neural networks to not only avoid the need for an exhaustive search for the inband nonlinearities expression required by the polynomial-based model but also to achieve improved cancellation accuracy. Simulation results on a 3-channel receiver demonstrate that the NN-based CDP algorithm achieves improved communications signal-to-noise ratio (SNR) in comparison with conventional cancellation techniques including multi-channel decisions feedback cancellation (MCDFC) and transversal feedforward NN-based topologies. The bit-error-rate (BER) performance comparison is made between the NN-based and the polynomial-based CDP algorithms, which demonstrates that the NN-based CDP algorithm achieves comparable bit-error-rate (BER) performance to the polynomial-based model counterpart without significantly increasing complexity for moderate AFE nonlinearities. Moreover, it offers enhanced BER performance for pronounced AFE nonlinearities but with a considerable increase in complexity.

**Index Terms**—Multi-channel receiver, nonlinearities cancellation, machine learning, neural network.

## I. INTRODUCTION

THE rapid expansion of data generation necessitates new paradigms capable of accommodating higher communication data rates in wireless and wireline transceivers, expanding over the popularity of multi-channel receiver architectures. These designs enhance spectral efficiency by dividing channel bandwidth into subchannels, allowing for high data rates through multi-tone or multi-band transmission [1]–[3]. However, the harmonic distortions and the inter-modulation products introduced from the nonlinear characteristics of the receiver AFE and the crosstalk among channels cause degradation in system BER performance. Considering the challenges in terms of flexibility, adaptability, and power consumption

faced by analog linearization techniques, it is desirable to implement the nonlinearity cancellation in the digital domain. Conventional digital nonlinearity cancellation techniques use a linear reference receiver with least mean square (LMS) filters to adaptively reproduce the nonlinearity distortions, which are then subtracted from the main receiver [4]–[7]. However, challenges remain in implementing these techniques effectively across multi-channel receivers, particularly with the growing number of channels and the need for linear reference paths.

Recently, neural networks (NNs) have drawn much attention from researchers due to their strength in pattern recognition and complex system modeling. Neural networks have been investigated as a promising behavioral model for nonlinear distortions [8]–[11]. In [9], the feed-forward NN canceler was proposed to mitigate the nonlinear interference in full-duplex transceivers. In [10], a low-complexity NN structure with two neurons in the first hidden layer is proposed to cancel self-interference with nonlinearities and memory effect. In [11], a two-step nonlinearity cancellation scheme is proposed, where the nonlinearity distortion is firstly reconstructed using the transmit signal and a trained neural network and then subtracted from the received signal in the digital domain.

In this paper, we build upon our previous work on the CDP algorithm for multi-channel nonlinearity cancellation by incorporating neural networks into its framework. The CDP algorithm iteratively evaluates output symbols from each channel, employing them in successive channels to mitigate nonlinearities within a feedback loop until convergence across all channels is attained. Previously, we relied on a polynomial-based model to estimate inband nonlinearities, deriving nonlinearity components through symbolic expressions. Here, we aim to substitute the polynomial-based model with trained neural networks. We investigate the nonlinearity cancellation performance of this NN-based CDP algorithm against other approaches utilizing neural networks, such as NN-based MCDFC and feedforward NN techniques, through simulations. Additionally, we compare the performance of polynomial-based and NN-based CDP algorithms, demonstrat-

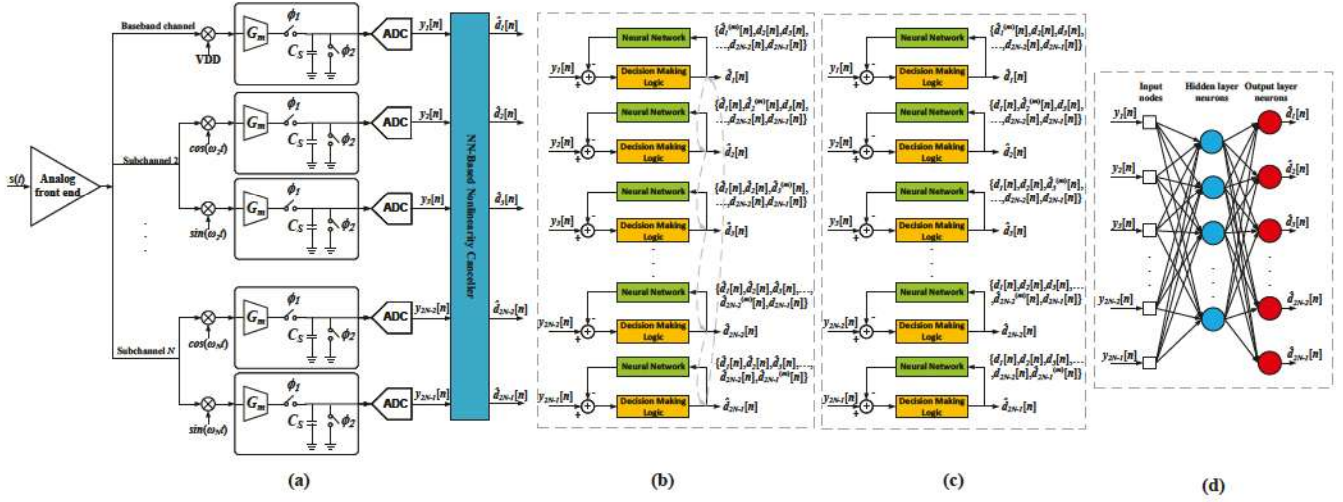


Fig. 1: (a) Block diagram of the multi-channel receiver with nonlinearity cancellation architecture using: (b) NN-based CDP, (c) NN-based MCDFC, (d) Feedforward NN.

ing that the NN-based CDP algorithm achieves comparable BER performance to its polynomial-based model counterpart without significantly increasing complexity for moderate AFE nonlinearities. Moreover, it outperforms the polynomial-based CDP algorithm for pronounced AFE nonlinearities, albeit with a manageable increase in complexity.

## II. SIGNAL MODEL, RECEIVER ARCHITECTURE, AND NN-BASED CDP ALGORITHM

The architecture of the multi-channel receiver is shown in Fig. 1(a), which is designed to detect a multi-band signal. The baseband channel is a single path configured to detect a pulse amplitude modulation (PAM) signal, whereas the remaining subchannels  $i = 2, \dots, N$  have both I&Q paths configured to detect a quadrature amplitude modulation (QAM) signal. The multi-band signal  $s(t)$  to the input of the multi-channel receiver can be expressed as:

$$s(t) = x_1(t) + \sum_{i=2}^N \text{Re}\{c_i(t)e^{j\omega_i t}\} \quad (1)$$

where  $x_1(t)$  is a PAM signal, and  $c_i(t)$  are QAM signals that are up-converted and transmitted through the higher frequency sub-bands with center frequency  $\omega_i$ . The QAM constellation points can be expressed as  $c_i(t) = x_{2i-2}(t) + jx_{2i-1}(t)$ , where  $x_{2i-2}(t)$  and  $x_{2i-1}(t)$  are the equivalent PAM signals corresponding to the in-phase and quadrature component of the QAM signal. This multi-band signal passes through the AFE, which is used to partially compensate for the channel loss, mixer, integrator, and finally the analog-to-digital converters (ADCs) before becoming the input to the digital signal processor (DSP), which is designed to cancel the nonlinearity distortion introduced by the AFE.

To consider the nonlinearities of the AFE, the samples received at the output of the ADC for each receiver path can

be expressed as:

$$y_l[n] = G\left(\sum_{p=1}^P \alpha_p s_l[nT]^p\right) \quad (2)$$

in which, the transmitted signal after down-conversion through each path is represented by  $s_l[nT]$ ,  $P$  is the order of the nonlinearity polynomial,  $\alpha_p$  represents the  $p$ th order nonlinearity parameter, and the function  $G()$  is the transfer function of the integrator which practically filters out high-frequency components that fall beyond the baseband bandwidth. Since the even-order nonlinearities vanish when the fully differential structures are used, and the nonlinearity profile obtained through circuit simulation can be accurately represented by incorporating only third-order nonlinearities, the third-order harmonic distortion, and the third-order intermodulation products (IM3) falling in the baseband are considered for mitigation throughout this study. The analysis and simulations presented herein exclude the influence of residual channel loss, which was not fully compensated for by the AFE. These effects can be effectively mitigated through digital equalization. Our focus remains on investigating NN-based nonlinearity cancellation for multi-channel receivers.

In Eqn. (2),  $y_l[n]$  can be decomposed as:

$$y_l[n] = x_l[n] + \tilde{x}_l[n], \quad l \in [1, 2N-1] \quad (3)$$

as mentioned above,  $x_l[n]$  denotes the PAM symbols transmitted through each path, and  $\tilde{x}_l[n]$  represents the inband nonlinearity distortions. As depicted in Fig. 1(b), the CDP algorithm operates as follows: Nonlinearity cancellation proceeds channel by channel, with subchannels processed path by path. Given the low likelihood of simultaneous output errors in multiple paths, accurate outputs from certain paths can be utilized to correct errors in others. For each path, every constellation symbol  $\hat{d}_l^{(m)}[n]$  associated with the detected symbols  $\hat{d}_l[n]$

from other paths undergoes evaluation to estimate nonlinearity distortions, which are subtracted from the received samples through the feedback loop. The constellation symbol that yields the minimum error with the nonlinearity cancellation result is considered the temporary decision  $\hat{d}_l[n]$  on  $x_l[n]$ . The detected symbol  $d_l[n]$  is then replaced by  $\hat{d}_l[n]$  and utilized by subsequent paths for their nonlinearity cancellation. This iterative process continues until  $\hat{d}_l[n]$  for all data paths converge.

The nonlinearity distortion of each path  $\tilde{x}_l[n]$  is approximated using a neural network. Given the variability of nonlinearity distortion across different data paths, a unique neural network is assigned to each path. The input of the neural network has  $(2N-1)$  nodes to accommodate the transmitted symbols for all paths, which is succeeded by one hidden layer and the output layer. The number of the neurons in the hidden layer can be adjusted with each neuron employing the rectified linear unit (ReLU) function, denoted as  $\text{ReLU}(x) = \max(0, x)$ , which is the most widely-used activation function considering its effectiveness for implementation. Fig. 2 shows the implementation detail of the NN-based feedback cancellation, the nonlinearities estimation  $\tilde{x}_{l,NN}[n]$  can be expressed as:

$$\tilde{x}_{l,NN}[n] = \sum_{k=1}^K w_k^{[2]} \text{ReLU} \left( \sum_{r=1}^{2N-1} w_{rk}^{[1]} o_r(X) + b_k^{[1]} \right) + b^{[2]} \quad (4)$$

where  $X$  is the input vector to the NN with  $2N-1$  dimension, and  $o_r(X)$  denotes the output of the  $r$ th input node.  $w_{rk}^{[1]}$  is the weight from  $r$ th input node to the  $k$ th neuron with  $K$  neurons in total in the hidden layer,  $w_k^{[2]}$  is the weight from  $k$ th neuron in the hidden layer to the output node,  $b_k^{[1]}$  is the bias of the  $k$ th neuron in the hidden layer, and  $b^{[2]}$  is the bias of the single neuron in the output layer. The nonlinearities estimation  $\tilde{x}_{l,NN}[n]$  is then subtracted from the output of the ADC  $y_l[n]$  and used by the slicer, which serves as the activation function of the output neuron, to make a decision on the transmitted symbol  $x_l[n]$ .

Algorithm 1 shows the pseudo-code that implements the NN-based feedback cancellation with the CDP algorithm assuming a PAM-4 signal is transmitted through the baseband

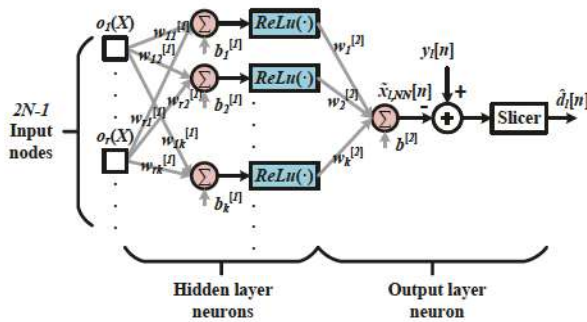


Fig. 2: Block diagram of the neural network-based feedback cancellation.

#### Algorithm 1 Neural-Network-based Feedback Cancellation with Channel Decision Passing Algorithm

**Input:** Vector of received samples after digitization of ADCs,  $\mathbf{Y} = [y_1[n], y_2[n], \dots, y_{2N-1}[n]]$ ;  
**Output:** Decisions with NN-based feedback nonlinearity cancellation,  $\mathbf{D} = [\hat{d}_1[n], \hat{d}_2[n], \dots, \hat{d}_{2N-1}[n]]$ ;  
1: setting detection level:  $\hat{d}_l^{(1)}[n] = -\frac{VFS}{2}$ ,  $\hat{d}_l^{(2)}[n] = -\frac{VFS}{6}$ ,  $\hat{d}_l^{(3)}[n] = \frac{VFS}{6}$ ,  $\hat{d}_l^{(4)}[n] = \frac{VFS}{2}$ ,  $l \in [1, 2N-1]$ ;  
2: Initialize output vector with detected symbols without feedback cancellation applied yet:  
 $\mathbf{D}_{out} = [d_1[n], d_2[n], \dots, d_{2N-1}[n]]$ ;  
3: **while** true **do**  
4:   **for**  $l = 1$  to  $2N-1$  **do**  
5:     **for**  $m = 1$  to 4 **do**  
6:       Generate input vector for the neural network,  
 $X^{(m)} = [\hat{d}_1[n], \dots, \hat{d}_l^{(m)}[n], d_{l+1}[n], \dots, d_{2N-1}[n]]$ ;  
7:       Calculate nonlinearities  $\tilde{x}_{l,NN}^{(m)}[n]$  based on Eqn. (4);  
8:        $\tilde{y}_l^{(m)}[n] = y_l[n] - \tilde{x}_{l,NN}^{(m)}[n]$ ;  
9:        $e^{(m)} = |\tilde{y}_l^{(m)}[n] - \hat{d}_l^{(m)}[n]|$ ;  
10:     **end for**  
11:     Find the index  $\min$  of the minimum  $e^{(m)}$ ;  
12:      $\hat{d}_l[n] = \hat{d}_l^{(\min)}[n]$ ;  
13:   **end for**  
14:   **if**  $\mathbf{D} = \mathbf{D}_{out}$  **then**  
15:     Break while loop;  
16:   **else**  
17:      $\mathbf{D}_{out} = \mathbf{D}$ ;  
18:   **end if**  
19: **end while**

channel and QAM-16 is transmitted through the rest subchannels. In this way, a PAM-4 signal is transmitted through each data path considering the full-scale peak-to-peak range (VFS) of the symbol.

In this study, we show the superior performance of the CDP algorithm in combination with NN-based feedback cancellation in reducing nonlinearity distortion when compared to two other NN-based techniques: the MCDFC and a feed-forward NN approach. The NN-based MCDFC technique is depicted in Fig. 1(c). This method uses neural networks in the feedback nonlinearity cancellation with the decisions made concurrently in each channel, without the decision-passing process. Moreover, the feedforward neural network technique, depicted in Fig. 1(d), employs a neural network in a transversal feedforward manner to mitigate nonlinear distortion by mapping distorted samples to the desired outputs. However, for a limited number of neurons, the NN-based feedback cancellation provides better performance than the feedforward-based NN nonlinearity reversion, because the feedback-based solution efficiently solves the front-end

feedforward nonlinearities, particularly for severe nonlinearity distortion. The effectiveness of these NN-based approaches in mitigating nonlinearity distortion will be validated through simulation results in the following section.

### III. SIMULATION RESULTS

In this section, we show the performance of the CDP algorithm with nonlinearity NN-based feedback cancellation. The simulations were conducted in MATLAB, leveraging the machine learning and parallel computing toolboxes to facilitate neural network training and deployment, utilizing a single Nvidia 3080s GPU for computational support.

In the simulation model, a 3-channel receiver is configured to detect a PAM-4 signal through the baseband channel and QAM-16 signals through 2 higher frequency channels to achieve a 64 Gigabit per second (Gbps) transmission rate, such that each data path is processing an effective PAM-4 signal with 6.4GHz bandwidth. The neural networks are trained using the Adam algorithm with 1E5 symbols from all channels. Moreover, the number of the training Epoches is set to 10 with a batch size of 16.

Fig. 3 shows the communications SNR comparison results of a 3-channel receiver employing various nonlinearity cancellation methods as the function of input third-order intercept point (IIP3) with 20dB  $E_b/N_o$ . Here,  $E_b$  represents the energy per information bit, assuming VFS of 1V, while  $N_o$  denotes the power spectral density of the noise at the input. The communications SNR is expressed as follows:

$$SNR_{COMMS} = \left( \frac{1}{2b} \right) \frac{P_s}{P_n + \sigma_{NLres}^2} \leq \frac{E_b}{N_o} \quad (5)$$

where  $b$  is the number of bits per symbol,  $P_s$  is the received baseband signal power,  $P_n$  is the noise power considering the input-referred noise shaped by the magnitude response of the AFE while ignoring other noise contributors, and  $\sigma_{NLres}^2$

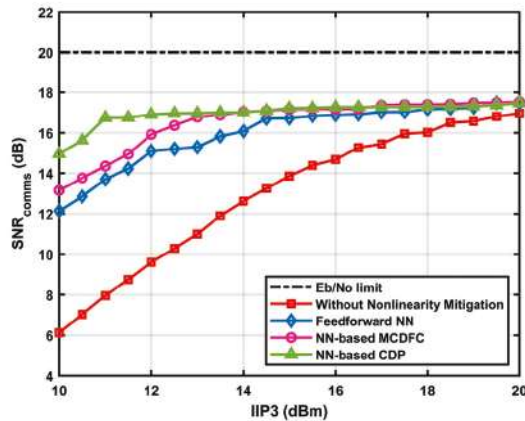
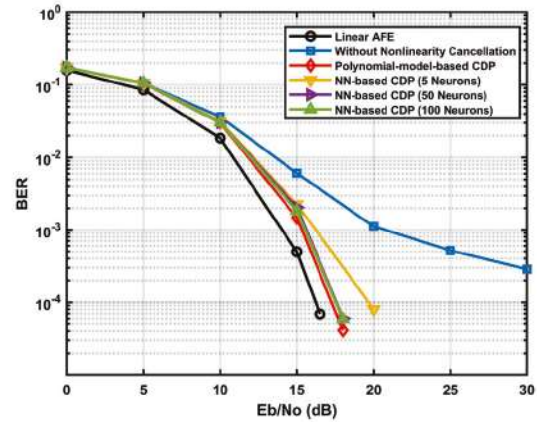


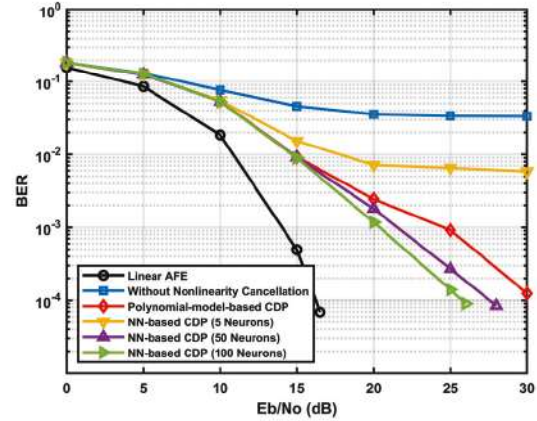
Fig. 3: Communications SNR vs. IIP3 comparison between NN-based CDP, NN-based MCDFC, and Feedforward NN with VFS = 1V, 50 neurons in the hidden layer, and  $E_b/N_o = 20$ dB.

denotes the variance of the residual nonlinear distortions post-mitigation. In Fig. 3, all NN-based nonlinearity mitigation techniques used neural networks with 50 neurons in their hidden layers. The results show that all techniques significantly enhance the communications SNR compared to a receiver that does not incorporate nonlinearity mitigation. However, the NN-based CDP algorithm provides noticeable communications SNR improvement over the NN-based MCDFC and feedforward NN techniques in the low IIP3 regime. Specifically, when the IIP3 is 11dBm, the NN-based CDP algorithm provides a communications SNR improvement of 2.4dB over the NN-based MCDFC and a communications SNR improvement of 3.0dB over the feedforward NN. This result shows the NN-based CDP's potential to reduce linearization needs in multi-channel receivers' AFEs, ensuring reliable BER performance in the presence of severe nonlinearity distortion.

Fig. 4 shows the BER performance comparison of the CDP algorithm as the function of  $E_b/N_o$  using the polynomial-based model and neural networks for feedback nonlinear-



(a)



(b)

Fig. 4: BER vs.  $E_b/N_o$  comparison between the polynomial-based and the NN-based CDP with VFS = 1V, and (a) IIP3 = 13dBm, (b) IIP3 = 10dBm.

ity cancellation, respectively. Fig. 4(a) displays outcomes for a scenario with an IIP3 of 13dBm. Under these conditions, the polynomial-based CDP algorithm surpasses the NN-based CDP algorithm in performance considering the polynomial-based model provides accurate nonlinearities expression through the symbolic analysis. However, enhancing the NN-based CDP algorithm's efficacy is possible by augmenting the count of neurons within the hidden layer. Notably, a neural network configured with 100 neurons is capable of achieving a BER performance comparable to that of the polynomial-based CDP.

Fig. 4(b) showcases outcomes for a condition with an IIP3 of 10dBm. Under these circumstances, the NN-based CDP algorithm, utilizing configurations of either 50 or 100 neurons, outperforms the polynomial-based CDP algorithm. This performance advantage stems from the AFE's compromised nonlinearity profile, leading to a reduction in the signal-to-noise and distortion ratio (SNDR) of received samples. The consequent lower SNDR amplifies the chance of simultaneous errors in outputs from various paths. This situation renders the polynomial-based CDP more prone to settling on local optima in its decision-making process across all data paths. In contrast, the neural network is trained with data affected by both noise and nonlinearities, enabling the NN-based CDP to effectively navigate the increased probability of simultaneous errors and achieve convergence to the global optimum during the channel-decision-passing process. With 10dBm IIP3, the NN-based CDP, utilizing a neural network with 50/100 neurons in its hidden layer demands an  $E_b/N_o$  of 27/25.5 dB, respectively, to attain a BER of  $10^{-4}$ . In comparison, to achieve equivalent BER performance, the CDP based on a polynomial-based model necessitates an  $E_b/N_o > 30$ dB.

In a 3-channel receiver, the estimation of nonlinearities for each path with the polynomial-based model requires 27 multiplications. Meanwhile, with 5 input nodes, an NN with a 5-neuron hidden layer needs 30 multiplications and an additional 5 comparison operations for the ReLu function, assuming full connectivity between layers. However, Fig. 4 shows that only neural networks with 50/100 neurons in the hidden layer achieve comparable or improved BER performance compared to the polynomial-based model at IIP3 values of 13/10 dBm, respectively, significantly increasing the complexity to 300/600 multiplications with 50/100 comparison operations, respectively. The advantage of using the NN approach is not just the performance gains but also the neural network's ability to automatically estimate nonlinearities through training. This feature becomes particularly important as the number of channels increases, making the search for nonlinear expressions through symbolic algebraic computations using the polynomial-based model impractical.

#### IV. CONCLUSION

This paper explored the effectiveness of nonlinearity mitigation in a multi-channel receiver through the use of NN-based feedback cancellation with the CDP algorithm, comparing it against the NN-based MCDFC and feedforward neural

network techniques. The simulation results highlight the NN-based CDP algorithm's superior capability in enhancing the communications SNR, particularly in AFEs with a low IIP3. The research also examines the tradeoff between performance and complexity when choosing between polynomial-based and NN-based CDP approaches. Although with a significant increase in complexity, the NN-based CDP, utilizing a neural network with 50/100 neurons, achieves better BER performance compared to the polynomial-based model, especially when the  $E_b/N_o$  exceeds 20dB in scenarios with significant nonlinearity distortion (IIP3 = 10dBm). The NN-based CDP algorithm offers on-the-fly adaptability that makes it very suitable for use in multi-channel receivers with an expanding number of channels.

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