Simultaneous Echo Cancellation and Upstream Signal Recovery using Deep Learning in Full-duplex DOCSIS Systems

A Technical Paper prepared for SCTE•ISBE by

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Introduction

Full-duplex DOCSIS has been encountering a continuous uphill battle to double the channel capacity through resource sharing of uplink and downlink channels. As the downstream and upstream are delivered via the same spectrum at the same time, co-channel interference in the form of internal coupling, micro-reflections or echoes becomes a formidable challenge. To ensure the proper operations of full-duplex DOCSIS, echo cancellation is an urgently needed technique. Typically, it involves analog cancellation to lower the power level of the major echoes below the analog-to-digital converter (ADC) dynamic range, while digital cancellation is followed to remove the residual echoes ensuring a sufficient modulation error ratio (MER).

Many conventional echo cancellers are realized via a subtraction scheme, which implies the receiver is operating linearly. However, this limits the transceiver operation margin and the achievable MER. As the power of the desired and the echo signal increase, the receiver front-end may be driven away from its linear operation range and introduce nonlinear impairments. The crosstalk among the echoes and the desired upstream signals would degrade the echo cancellation performance. Thus, a simple subtraction-based cancellation is no longer sufficient.

In this paper, we propose a deep neural network (DNN) based method to simultaneously cancel the echoes and recover the upstream signal. Both the received signal and the known downstream signal will be fed into the DNN processer, and the DNN output is the recovered upstream signal. The DNN is an efficient method to mitigate nonlinearities because of the implemented nonlinear activation function at each hidden layer. After proper initial training, the DNN-based canceller can achieve an excellent upstream signal recovery and outperform the conventional digital cancellation schemes. Moreover, the on-demand dynamic training can be performed implicitly without impacting the regular DOCSIS system operation. This novel approach would dramatically improve the recovered upstream signal quality and increase the capacity of the DOCSIS. This paper is organized as follows. Section 1 reviews the background of echo cancellation in full-duplex (FDX) DOCSIS and the conventional methods' limitation. Section 2 introduces the concept of deep learning and the principles of DNN to realize echo cancellation. Section 3 demonstrates a proof-of-concept experiment and results analysis of DNN based echo canceller.

Content

1. Echo Cancellation in FDX DOCSIS

In the current cable access network, frequency division duplex (FDD) is implemented to provide various services to the cable subscribers. With FDD, the available cable spectrum is divided into non-overlapping parts for downstream and upstream, respectively. Different frequency splits have been defined including low split, mid split and high split. However, even with 5 MHz -204 MHz available spectrum of high split for upstream traffic from the cable modem (CM) to cable modem termination system (CMTS), it's still not sufficient to accommodate the exploding growth of bandwidth demanding services like AR/VR gaming, high-resolution video streaming. Besides, the high split also reduces the available spectrum to downstream traffic. To address the limited spectrum of cables and increase the spectrum usage efficiency, FDX was firstly introduced as DOCSIS 3.1 Full Duplex and latterly rebranded as part of DOCSIS 4.0 [1]. Unlike the frequency division multiplexing (FDM), the downstream spectrum could be reused by the upstream traffic without sacrificing the downstream bandwidth. In theory, the FDX DOCSIS allows overlapping spectrum between downstream and upstream traffic. Considering the 1.8 GHz full spectrum of the cable plant, the coax network bandwidth could potentially be doubled to 3.6 GHz. Though the appealing advantages of FDX DOCSIS, it suffers from various implementation challenges. One of the most significant challenge is the self-interference from the CMTS (Remote-PHY, RPD node) transmitter to its receiver. The system impairment due to self-interference is severe in FDX as the upstream and downstream share the same frequency spectrum, which cause co-channel interference. The self-interference arises from the internal coupling as well as the echoes in the forms of micro-reflections due to impedance mismatch at the taps as shown in Figure1.

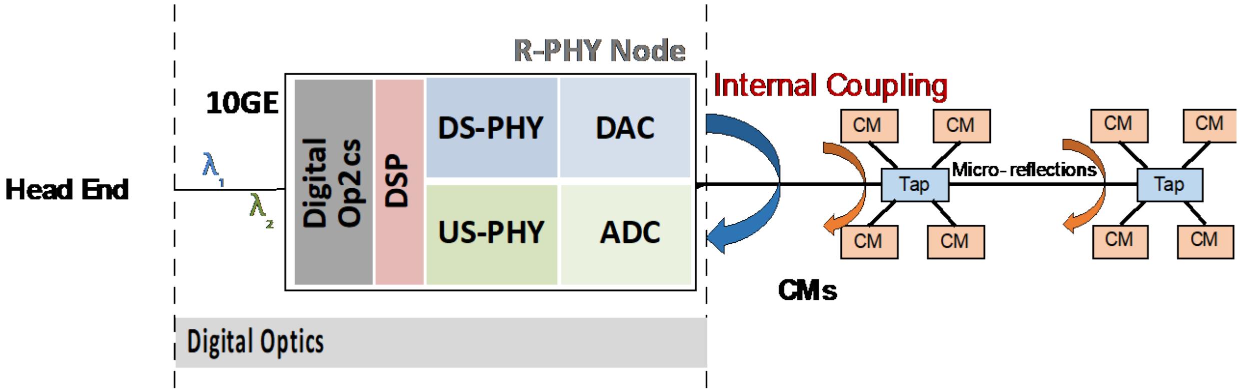

Figure 1 – Illustration of Self-Interference in FDX DOCSIS.

Since the downstream signal has a much larger power compared with the upstream signal, the received upstream signal will be overwhelmed in the spectrum if there's no sufficient isolation. As the interfering down-stream (DS) signal is in-band, it cannot be directly removed by a radio frequency (RF) filter. Therefore, echo cancellation is necessary at the RPD-equipped node to cancel the self-interference and realize the FDX transmission in the cable network. It's typically assumed that N+0 network topology is necessary to support FDX DOCSIS as bidirectional FDX amplifier is associated with dramatic design implications [2]. N+0 topology imposes all passive RF components which can support bi-directional analog RF transmission based on Lorentz reciprocity theorem. Such that the FDX operation is possible without the expensive replacement on the already deployed cables and taps.

The conventional echo cancellation techniques in FDX DOCSIS split into two process, namely, Analog cancellation and digital cancellation. The logistics behind the split is to accommodate the limited dynamic range of the ADC at the node receiver. The power level of the reflections in the FDX spectrum can be more than 15 dB higher comparing to the desired upstream signal [2]. Applying analog cancellation before receiving by the node receiver can significantly relieve the saturation effect of ADC and improve the effective MER for the upstream signal detection. Figure 2 shows the typical setup and process for echo cancellation in FDX DOCSIS. The analog echo canceller takes a copy of the downstream signal and tunes its phase and magnitude to create a canceling signal with the same amplitude but with 180-degree phase difference. As the actual echo signals are from various sources and different locations, the multiple echo paths with different amplitude and phase are tracked and estimated in the digital domain and then converted into analog domain for cancellation using a DAC. After the analog cancellation is performed, digital cancellation is followed to further suppress the echoes using tracked/computed echo cancellation coefficients. The conventional echo canceller assumes that the self-interference (SI) can be removed by subtraction. However, this assumption doesn't hold true when there's nonlinearity at the receiver of the RPD. In realistic FDX implementation, an echo cancellation method which can mitigate the nonlinear impairments is necessary.

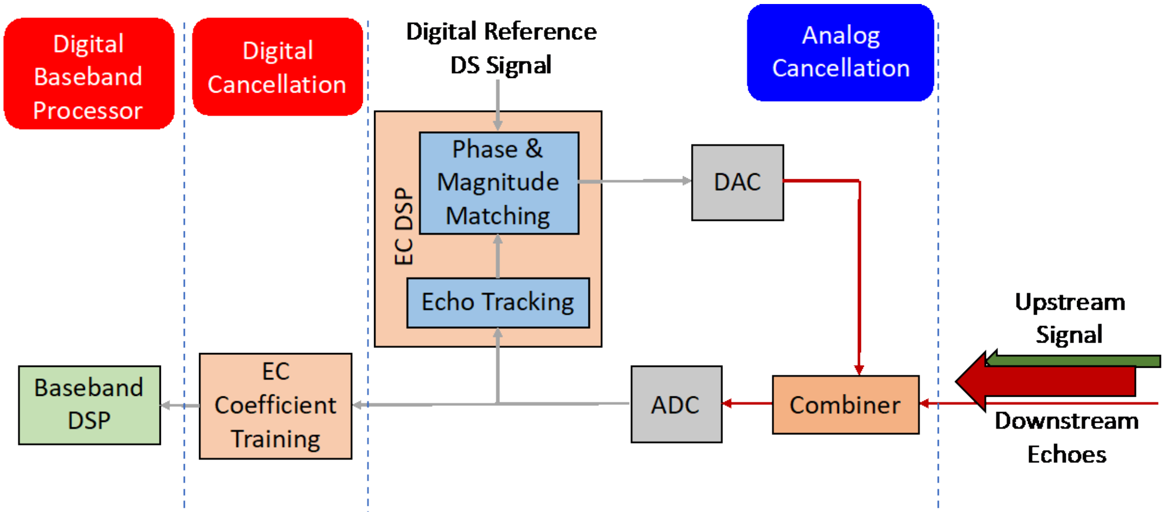

Figure 2 – Conventional Echo Canceller Structure and Process.

2. Deep Learning Recap and DNN-based Echo Canceller Principles

Deep learning has attracted tremendous interest from research and industry implementation. It is a sub-field of machine learning and it's based on artificial neural network with representation learning including supervised, semi-supervised and unsupervised. Deep learning performs excellently in image/video recognition, natural language processing and gaming. Beyond those conventional applications, deep learning also shows promising capability in dealing with challenges in wired/wireless communication, like multi-level signal recovery and adjacent channel interference mitigation [3-4]. Moreover, due to the booming development of neural network training algorithm, the training efficiency is significantly improved, while transfer learning can further reduce the required training time when there are any dynamic effects. Once the neural network is properly trained, the DNN inference is fast with low complexity as only simple matrix multiplications are required. Besides, the DNN can be implemented using general hardware like GPU, which provides the DNN with high scalability and low implementation cost.

To solve the aforementioned challenges in echo cancellation, we design and implement a DNN-based echo canceller to eliminate the nonlinear echo and the nonlinear crosstalk at the receiver jointly. The echo canceller will be implemented at the RPD. Here, we take the received signal and the known SI signal as the input to the DNN, while the output of the DNN is the recovered upstream signal of interest. The proposed DNN structure and parameters are shown in Figure 3, which consists of 3 hidden layers with 64, 32, and 16, respectively. The input layer has 41 neurons like the taps of a non-casual filter, while the output has 1 neuron representing the recovered signal-of-interests (SOI). The nonlinear rectified linear unit (ReLU) activation function is used at each hidden layer. In this case, the mapping between the received signal to SOI is not by subtraction of SI anymore. The nonlinear correlations between SI and SOI and the nonlinear distortion on the SI signals are also eliminated by the DNN after learning the sophisticated mapping. Besides, the DNN canceller realize the simultaneous echo cancellation and SOI recovery, greatly simplify the conventional two-step process.

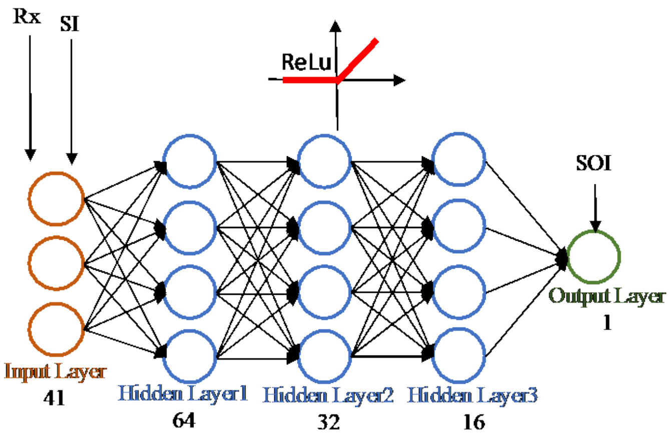

Figure 3 – Structure and parameters of proposed DNN echo canceller.

Another benefit of the DNN canceller is its minimal impact on regular service during its training process. As shown in Figure 4, due to the limited modeling capability, the conventional digital signal processor (DSP) needs to be built in a block structure. The echo information is firstly estimated and removed from the received uplink signal with echo. After the echo canceller, a baseband DSP is conducted to recover the SOI subsequently. It is worth note that to obtain the accurate echo information, an additional training period is required in the conventional DSP fashion. In other words, certain time slots are preserved for DS signal transmission only, in such period, the upstream (US) signal is halted, and the DS training signal occupies all the available RE, resulting in a low channel utilization. On the other hand, the proposed DNN based decoder can break the DSP block structure. Most importantly, aided by the sophisticated DNN decoder, the dedicated training period can be removed which allows an implicit training without impacting system operation. Therefore, full-duplex transmission can be achieved all the time.

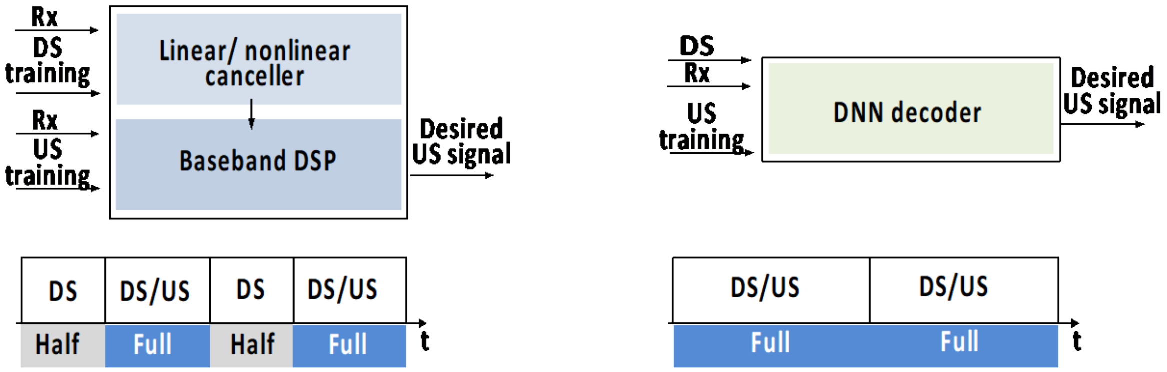

Figure 4 – Comparison of DSP structure and time domain data management. (a) linear and nonlinear cancellers (b) DNN decoder.

3. Experimental Setup and Results Analysis

The experimental setup of the orthogonal frequency division multiplex-based (OFDM) full-duplex transmission system is illustrated in Figure 5. A 16-GSa/s arbitrary waveform generator (AWG) is employed to generate the downlink echo and the desired uplink signal. To evaluate the impairment due to the interference power from the reflected echo, a 10-dB attenuator cascaded by a 35-dB gain amplifier are applied to boost the downlink signal. Echo signal and the desired signal are combined via a power combiner before entering a 10 GSa/s real-time scope (RTS). Both echo and uplink signal are offline encoded and decoded via Matlab. The typical OFDM processing is employed. The FFT size is 2048 and the subcarrier spacing is set as 1.92 MHz. The bandwidth of echo is fixed as 990MHz and the desired uplink signal bandwidth under tested are 90, 450, and 990 MHz, respectively. The downstream transmitted power is ranging from -10 to -18 dBm before the power amplifier.

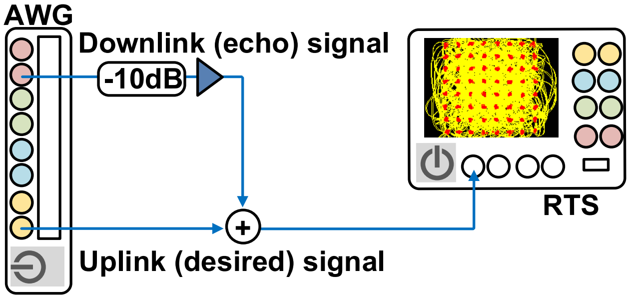

Figure 5 – Experimental setup of the OFDM-based full-duplex transmission system.

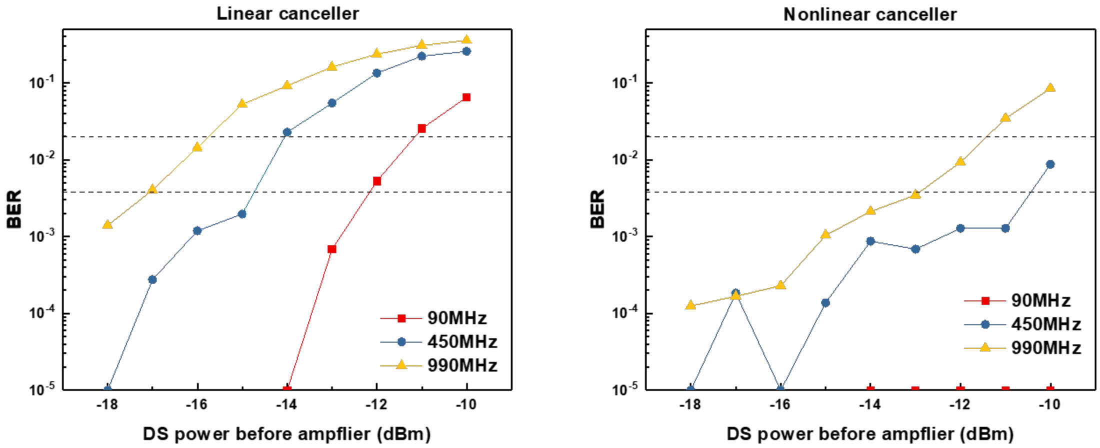

Figure 6 – BER performance versus interference with (a) linear (b) nonlinear cancellers.

As one can note that in Figure 6, the received BER performance is getting worse as the bandwidth of uplink increasing. This can be understood since the output Vpp of the desired signal, i.e., uplink, is fixed by the AWG as 1 V. Thus, as the bandwidth increasing, the per subcarrier SNR is decreased. Meanwhile, the BER is getting worse when the DS power increasing because the echo impairment is also increasing for the uplink signals in this case. On the other hand, the BER performance with nonlinear canceller, i.e., Volterra equalizer, always outperforms the linear canceller, i.e., minimum mean square error (MMSE), at the cost of a much higher DSP complexity. In the case of 90-MHz US, the BER of nonlinear canceller performs irrelevant to the power of echo interference.

The DNN decoding is a data driven processing. In this demonstration, the received signal is decoupled as training set, validation set and test set. Each set of data occupies one third of the received signal. The training set is firstly used to train the optimal weights and bias of the DNN, and the validation set is employed to validate the behavior of the DNN model. The DNN model we designed has one input layer, three hidden layers, and one output layer. Activation function is $\mathrm{R}eLu(x)$ and the loss function is MSE. Optimizer employed in this experiment is Adamax which can ensure a faster and better convergence. After modeling, the test set would be processed by the trained DNN; while the training set result is also presented as a benchmark. It is worth to remind that DNN can cancel the SI and recover the SOI simultaneously, which enables full-duplex transmission.

As shown in Figure 7, the DNN decoding performance of 90 MHz US is similar to the nonlinear canceller. In this case, the DS information is not needed and thus all the RE can be fully utilized for the full-duplex operation. However, the performance of DNN drops quickly as the bandwidth increasing to 450MHz. DNN only outperforms the linear canceler in the strong interference range of DS power over -15 dBm, in such range, both DNN and linear canceler cannot achieve the FEC threshold requirement even with 20% overhand. This performance degradation may be caused by the insufficient vertical resolution of the received signal, since the peak to average power ratio (PAPR) increase proportional to the active subcarrier number. To circumvent this restriction, a straightforward method is reducing the active subcarrier number at the cost of reducing the bandwidth.

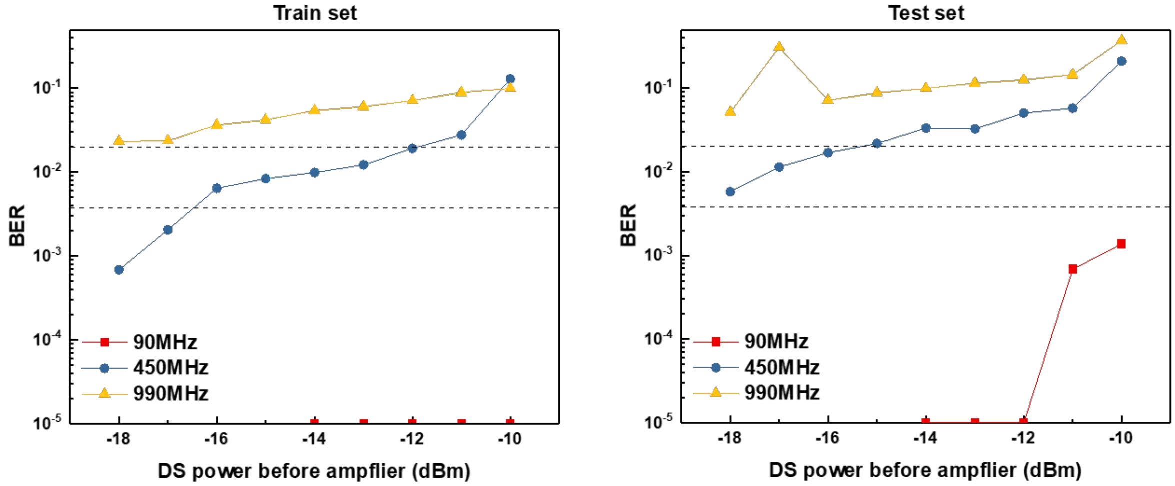

Figure 7 – BER performance verse interference with DNN decoder (a) train set (b) test set.

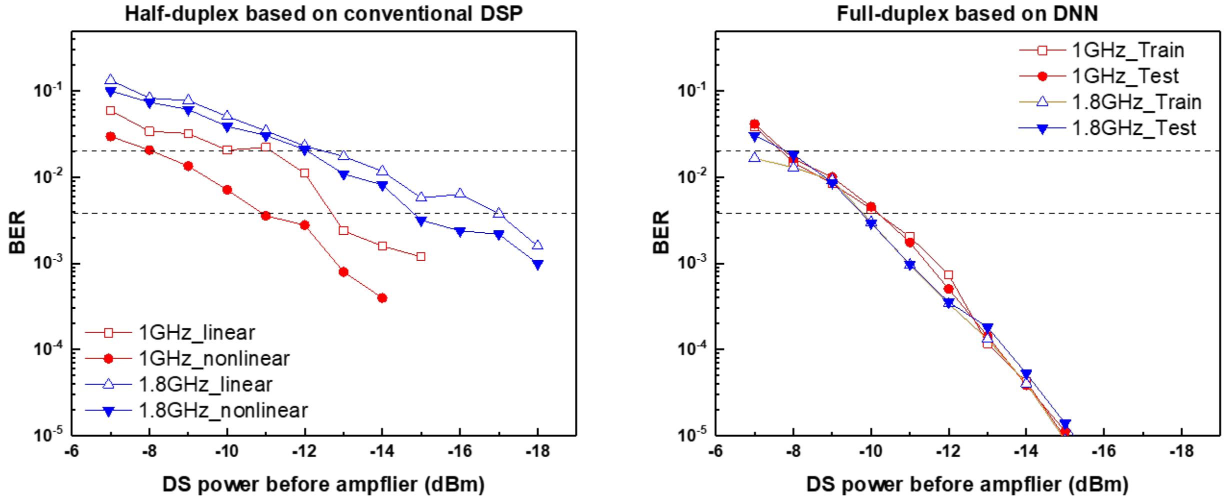

Figure 8 – Wideband echo canceller BER performance (a) conventional DSPs (b) DNN.

To get the better DNN performance and keep the transmission bandwidth, we can reduce the fast Fourier transform (FFT) size and active subcarrier number as well as increase the subcarrier spacing. Bandwidth under tested are 1GHz and 1.8GHz to comply with the DOCSIS 4.0 requirement. The active subcarrier number are 32 and 58, respectively. With the new settings, the US and echo have the same bandwidth for the FDX operation. the DNN canceller outperforms the conventional linear and non-linear DSPs in both scenarios as shown in Figure 8. The test set data performance is close to the training set, which implies no overfitting issue in the DNN process. The received performance is not sensitive to the bandwidth increment.

Conclusion

As cable access network service providers evolve toward N+0 architecture and FDX DOCSIS for higher capacity, the echo cancellation technique becomes a core enabler to ensure reliable and high-performance services. The DNN-based echo canceler offers a future-proofing solution for cable operators to satisfy the exponentially growing bandwidth demand without dramatic infrastructure change.

In this paper, we explain the working principles of the proposed DNN canceller and conduct a proof-of-concept experiment to verify its performance in SOI recovery comparing with Volterra-based nonlinear canceler and conventional linear canceler. Better BER performance is observed at any measured DS transmission power for both 1 GHz and 1.8 GHz bandwidth cases. The results show the DNN canceller is robust for different configurations and working conditions of the coaxial cable network. This means that the cable operators may effectively support FDX operation over the whole available DOCSIS 4.0 spectrum without significant update on the physical infrastructure.

Abbreviations

ADC	analog to digital converter
AWG	arbitrary waveform generator
BER	bit error rate
CM	cable modem
CMTS	cable modem termination system
DAC	digital to analog converter
dB	decibel
dBm	dB milliwatt
DNN	deep neural network
DOCSIS	Data Over Cable Service Interface Specification
DSP	digital signal processing
DS	down stream
EC	echo cancellation
EVM	error vector magnitude
FDD	frequency division duplex
FDX	full duplex
FEC	forward error correction
FFT	fast Fourier transform
GHz	gigahertz
HFC	hybrid fiber-coax

Hz	hertz
MER	modulation error ratio
MHz	megahertz
MMSE	minimum mean square error
MSE	mean square error
PAPR	peak to average power ratio
PHY	physical layer
QAM	quadrature amplitude modulation
QPSK	quadrature phase shift keying
R-PHY	remote PHY
RE	resource element
ReLU	rectified linear unit
RF	radio frequency
RPD	remote PHY device
RTS	real-time scope
Rx	received signal
SCTE	Society of Cable Telecommunications Engineers
SD-FEC	soft decision forward error correction
SI	self-interference
SNR	signal to noise ratio
SOI	signal of interest
US	upstream

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