RX Equalization for a High-Speed Channel based on Bayesian Active Learning using Dropout

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***Abstract*—Determining optimal equalization settings in high-speed bus design simulations is becoming more important due to increased complexity and data rates of current server systems, but it is also time and resource consuming. In this paper, a probabilistic machine learning technique, Bayesian Active Learning using Dropout (BAL-DO), is utilized to perform RX equalization and optimization to address this issue. Largest HEYE opening and corresponding equalization settings are obtained with high prediction accuracy without performing extensive time-domain analysis, thereby significantly reducing the cost of engineering time and computational resources.**

I. Introduction

The demand for faster data rates and more versatile functionality in computing systems results in more complex systems with a large number of components and interconnects. A key part of high-performance systems are board-to-board interconnects for the high-speed links which transmit signals between components on different boards. Such links can exist in between processors and other modules such as FPGAs, memory controllers and expanders. Due to the increase in complexity, signal integrity (SI) properties such as insertion loss (IL) and crosstalk (XT) can vary significantly from channel to channel, which complicates confirming the channel compliance for sign-off and production. To maximize and stabilize the performance of channels that contain cables, connectors and PCBs, channel equalization designed in I/O circuitry is required to have stronger capability and robustness. Various equalization schemes such as feed-forward equalizer (FFE), decision feed-back equalizer (DFE) and continuous time linear equalizer (CTLE) can be implemented on the transmitter (TX) side and the receiver (RX) side. A direct consequence of adding more equalization capabilities is the increased complexity of the I/O circuitry and larger design space for SI simulations. Normally, SI engineers need to perform time-domain simulations by sweeping most of the equalization settings to obtain desired eye sizes for different channel configurations. However, as the combinations of the equalization settings increase exponentially, sweeping through the entire design space becomes extremely time and resource consuming and, ultimately, impractical. It is critical for SI analysis to find an efficient method that can reduce the optimization time as well as resources and allow the designer to understand the preferred equalization settings for various channel configurations.

An intuitive idea is to apply machine learning (ML) techniques to these problems [1][2]. However, conventional ML methods are data hungry, and difficult to capture domain expertise. Equalization optimization with time-domain analysis requires intensive computational resources, limiting the amount of data being available in many cases. A probabilistic method that predicts a posterior distribution rather than deterministic predictions is a better candidate for limited training data scenarios. Recently, a novel ML technique based on Bayesian Active Learning (BAL) has been developed [3]. A new algorithm, Bayesian Active Learning using Dropout (BAL-DO) was proposed to achieve accurate data space exploration when learning data is limited. This has been tested on IBM's POWER9 channel, and successfully acquired the worst-case horizontal eye (HEYE) opening with high accuracy among large number of channels in minimum amount of time-domain simulations. The main advantage is the significant reduction of computational costs while maintaining high accuracy, and this has been demonstrated in [3] by comparing with other machine learning methods. In this work, the BAL-DO algorithm is extended to include RX equalization for a high-speed memory channel [4] to determine the equalization setting that provides the largest HEYE along with the confidence bounds of the resulting eye which is a key feature of BAL-DO.

The BAL-DO technique mainly consists of two parts, the optimization stage and the active learning stage, and they are combined associatively in the algorithm [3]. As the code starts with no training data, one set of initial training data is generated and fed into the program. In the optimization stage, the next sampling point is selected using Bayesian Optimization (BO) method with self-learning acquisition function strategy obtained using a Gaussian Process (GP) model. The goal for the active learning part is to minimize the uncertainty of the GP predictions for non-simulated equalization settings by selecting the setting that maximizes entropy. The information from both stages is combined in a single GP while using a dropout technique to prioritize optimization over learning [3]. The next sample is then evaluated using the simulation framework to get the corresponding HEYE, followed by re-training the GP and proceeding to the optimization stage again.

II. Simulation Procedure and Setup

The simulation framework in this paper is based on a high-speed differential channel passing signal from CPU to the memory buffer running at 32Gb/s NRZ. S-Parameters for the whole channel are first generated, time-domain simulations are then performed under various equalization setting combinations using an in-house tool to obtain the corresponding HEYE opening results. BAL-DO uses this framework to determine next equalization settings to be simulated in an automated fashion. At each simulation iteration, the GP is trained by using all the data obtained in previous iterations. The largest HEYE opening, the probability density function (PDF) of HEYE and a sensitivity

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analysis that ranks the equalization settings in terms of creating a variation in HEYE is then derived through the learned GP after a certain number of simulations.

In this work, the optimum eye opening is searched by varying the receiver equalizations which includes 4 different settings with their varied combinations defining certain frequency dependent RX peaking curves. These 4 different settings are: long tail equalizer (LTE) gain, LTE zero, and 2 peaks of CTLE. LTE gain and LTE zero have 8 setting options each, and 2 CTLE peaks have 16 setting options each. This results in total number of 16384 possible combinations of equalization settings for the RX equalization. Each combination contains 4 variables, and is defined as a single input vector, to be fed into the BAL-DO algorithm and call the in-house simulator, HSSCDR, to run the time-domain simulation. The main objective is to find the largest HEYE opening and its corresponding equalization settings, while the aforementioned sensitivity analysis and HEYE PDF are considered as secondary objectives. In addition, FFE and DFE are also included as part of TX and RX equalization, but their settings are auto-adapted in HSSCDR. The data rate in the simulation is set as 32Gb/s and the HEYE is found at BER=10^{-15}.

III. Simulation Results

Since the number of equalization combinations is large, 700 iterations are used in BAL-DO to ensure convergence, which is about 4.3% of total numbers of combinations. One single simulation iteration takes approx. 20 min, leading to the whole run to be completed in about 10 days. It will be seen later that significantly less numbers of iterations can be considered to arrive at convergence, which leads to considerably less time.

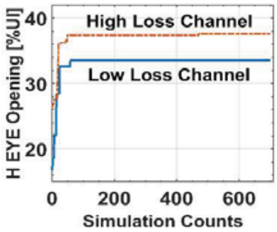

Fig. 1. Largest HEYE opening vs. simulation counts for high and low loss channels.

Different parameters from channel components such as lengths, manufacturing/packaging corners and impedance can be picked to form channels with different properties. To understand the performance of BAL-DO algorithm for channels with different properties, the optimization is performed for two channels with high loss and low loss (22.7 dB and 10.4 dB loss at 16GHz, respectively) for the same bus topology and results are compared. Fig. 1 shows the largest HEYEs derived from BAL-DO method for both high and low loss channels as simulation counts increase. HEYEs for both channels increase at early counts towards the optimal, reaching 33.5%UI at 59th simulation and 37.4%UI at 49th simulation for low and high loss channels, respectively, which corresponds to less than 1 day of CPU time. After that, largest HEYE for low loss channel remains unchanged till 700 simulations are done. For high loss channel, HEYE increased by 0.2%UI to 37.6%UI at 471st simulation, and then no change till finishing all 700 simulations. Note that in order to obtain this extra 0.2%UI, the algorithm takes approx. 6 extra days, thus the "trade-off" between excessive extra simulation time along with resources, and small amount of HEYE opening improvement needs to be considered and balanced. One may not need to do additional intensive simulations to only receive a tiny margin of improvement. It is worth noting that the largest HEYE opening for low loss channel is smaller than that of high loss channel. Possible reasons for that are: (1) increased insertion loss deviation -reflections- for the low loss channel and (2) RX peaking circuit design targeting high loss channel equalization thus causing over-equalization for the low loss channel.

The converging criteria of BAL-DO is when the maximum value of upper confidence boundary (UCB) is within a small margin of the largest HEYE found after each iteration. This guarantees the optimal value found has 95% confidence level to be the global optimum. Convergence curves with respect to number of simulations for low and high loss channels are shown in Fig. 2(a) and 2(b), respectively. At early iterations, max of UCBs are very large, meaning the prediction has large uncertainty and goal has not been met yet. As BAL-DO progresses to find the largest HEYE opening, two curves get closer, and both shows relatively good convergence after 100 iterations. Note that for the high loss channel, the gap between max UCB and Largest HEYE is larger than that of low loss channel after converging. This is due to equalization having more influence on HEYE opening of high loss channel than low loss one. As simulation counts increase, the gap becomes smaller, indicating prediction gets more accurate. To further verify, intensive simulations were done through HSSCDR and confirms that 37.6% UI is the best HEYE for the high loss channel.

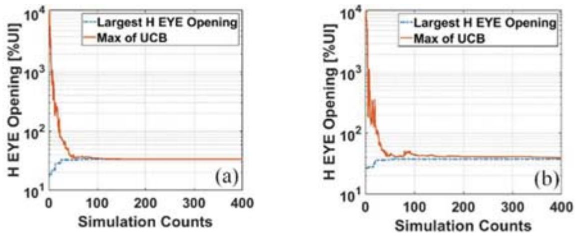

Fig. 2. Convergence for low (a) and high (b) loss channels

Values for RX equalization variables rendering optimal HEYE opening for different channels obtained from BAL-DO are listed in Table I.

TABLE I. RX equalization values for optimal HEYE opening

	LTE zero	LTE gain	Peak 1	Peak 2	Largest HEYE	Simulation Needed
low loss channel	2	2	1	1	33.5%UI	59
high loss channel	8	1	10	14	37.4%UI	49
	3	2	7	5	37.6%UI	471

The number of variables, and the number of values being swept in the pool of each variable, are the two main factors that affect the minimum iterations for BAL-DO to arrive at desired results though the former has higher impact. In this case, 4 RX equalizers are defined as variables, making this a 4-dimensional problem. As mentioned above, if the extra 0.2%UI improvement can be neglected for the high loss channel, 100 counts (0.6% of overall combinations) is enough to derive the largest HEYE with good accuracy and low uncertainty. As comparison, a previous BAL-DO test with 9 variables required to simulate 4-5% out of the overall combination pool [3]. For brevity, the rest of the paper deals with the high loss channel.

The PDFs of the high loss channel after 100 & 400 simulations are plotted and compared in Fig. 3. In both cases, the uncertainty values (blue histogram) at 37.4%UI are very low, and they are very close (0.0027 vs. 0.0022, as shown in the inset images), indicating that 400 iterations do not improve the accuracy too much as compared to 100 iterations. In addition, both PDF curves show that the distributions are left-skewed. especially after 400 iterations as in Fig. 3(b), meaning that the samples selected by BAL-DO are focused more on the larger EYE region, and this is consistent with the goal of finding largest HEYE. The uncertainty given as blue shading on the large HEYE side is steeper in Fig. 3(b) as compared to Fig. 3(a). This is because as the number of iterations increase, more training data are available for BAL-DO to improve the overall accuracy, especially in the large HEYE region.

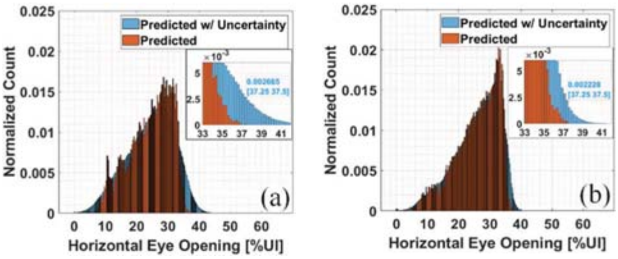

Fig. 3. PDF after 100 (a) and 400 (b) iterations.

BAL-DO algorithm starts with no training data initially, thus requires an initial input vector to generate a corresponding HEYE opening and form one set of training data. The variable combination pool including all combinations is generated by BAL-DO and remains unchanged, and the starting input vector is randomly selected by the algorithm from it. To understand the influence of the initial point selection, three different input vectors are manually picked and fed into BAL-DO for the high loss channel. Fig. 4 shows the largest HEYE openings with respect to simulation iterations by applying 3 different initial inputs. Low, mid and high index initial points denote the 10th, 8010th, and 16010th combinations in the combination array, respectively. Their corresponding values are listed in Table II.

TABLE II. EQUALIZATION VALUES FOR EACH INITIAL INPUT POINT

	LTE zero	LTE gain	Peak 1	Peak 2
10th point	1	1	1	10
8010th point	4	8	5	16
16010th point	8	7	13	9

As demonstrated in the left inset image in Fig. 4, when reaching 37.4%UI, simulation with low index initial point takes 49 iterations, mid index initial points run takes 59 iterations, and the one with high index initial point takes 79 iterations. This again indicates that 100 simulations are enough to achieve the objective regardless of initial point used. As the simulation count increase above 450, as shown in the right inset image of Fig. 4, all three runs eventually reach 37.6%UI. Again, the trade-off between tiny margin of improvement and excessive simulation time needs to be taken into consideration.

Sensitivity analysis is also performed after different simulation counts for the high loss channel. As shown in Fig. 5, CTLE peak 1 has the most influence on the HEYE opening as simulation counts increase. Meanwhile, as more training data becomes available as simulation counts increase, the area between UCB and lower confidence boundary (LCB) for each variable decrease, indicating the uncertainty over weights becomes smaller, hence prediction becomes more confident and accurate. Note that in Fig. 5(a), peak 1 has a slightly higher weight than peak 2. In this case, more training data are needed to distinguish the differences between them, and 150 iterations is enough to draw the conclusion instead of going up to 400.

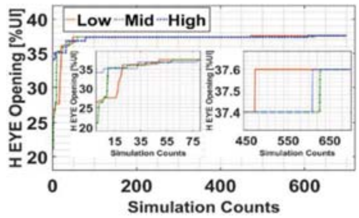

Fig. 4. Largest HEYE opening vs. simulation counts for BAL-DO different starting points.

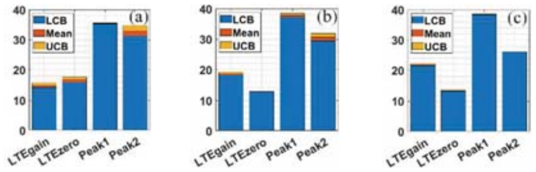

Fig. 5. Sensitivity for 100 (a), 150 (b), and 400 (c) simulation counts for high loss channel.

IV. Conclusion

Bayesian Active Learning using Dropout (BAL-DO) is extended to successfully perform efficient RX equalization optimization for high-speed channel design. Results show that for both high and low loss channels, main objective of finding largest HEYE openings and their corresponding equalization settings can be achieved within 100 simulations with good convergence and low uncertainly. With different initial input points, results still converge within 100 simulations, which is only 0.6% of overall equalization setting combinations. This significantly reduces engineering time and resources while maintaining high accuracy. The sensitivity analysis shows Peak 1 is the dominant variable and has higher influence on the HEYE opening. BAL-DO technique has great capability of using minimum resource to find global optima with high predictive accuracy, and it can be extended to different types of equalization problems with more variables.

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