Realization of Neural Network-based Optical Channel Equalizer in Restricted Hardware

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Abstract—We quantify the achievable reduction of the processing complexity of artificial neural network-based equalizers in a coherent optical channel using the pruning and quantization techniques. First, we explain how to correctly compute the complexity of the compressed equalizer in the DSP sense. Then, considering a basic neural network architecture, a multiplayer perceptron, we, for the first time, assess the complexity reduction attainable noticeable performance degradation, considering 30 GBd 1000 km transmission over a standard single-mode fiber. We demonstrate a possibility of reducing the equalizer’s memory up to by up to 95.7%, and the complexity up to 91.5%, without noticeable performance degradation. Finally, the compressed equalizer’s functioning is demonstrated experimentally using popular resource-constrained hardware: the Raspberry Pi, which would not have been possible without model compression.

Index Terms—Neural network, Nonlinear equalizer, Pruning, Quantization, Raspberry pi, Coherent detection.

I. INTRODUCTION

One of the major factors limiting the capacity of fiber-optic communication systems is the nonlinearity-induced transmission impairments [1], [2]. Among the variety of solutions proposed to deal with this problem [2], the approaches based on machine learning techniques are growing in popularity [3]–[7]. A number of neural network (NN) architectures have been studied so far, including the feed-forward structures like multi-layer perceptron (MLP) [6], [8], or the different variants of recurrent NNs (RNN) [6], [9], demonstrating their potential in the channel equalization task. However, the practical deployment of the real-time NN-based channel equalizers requires that their computational complexity is comparable or lower than that of the conventional DSP solutions [10]. Therefore, the computational complexity and memory consumption requirements of NNs are key factors during both the training and inference of NN equalizers. Regarding the NN training stage, different techniques have been developed to reduce the cost of this task in terms of time, energy, and required data [11]. Good performance of NNs is linked to the use of a large number of parameters that are adjusted to efficaciously unroll the complicated optical channel function. This increases both memory and computational power requirements, leading to increased energy and resource consumption [12], [13]. Thus, the use of NN-based methods becomes a challenge in applications like optical channel equalization, where the computational complexity emerges as a limiting real-time deployment factor [6], [9], [12], [14]. Nonetheless, many NNs may be simplified without affecting their performance much, thanks to well-known strategies such as pruning and quantization, which attempt to reduce the memory footprint of the model and its complexity [12], [13], [15]–[17]. In this paper, we apply pruning and quantization techniques for the reduction of the complexity and memory requirements of a coherent optical channel equalizer and show how to correctly compute such complexities.

II. COMPRESSING PROCESS ON NEURAL NETWORK EQUALIZERS

The pruning technique involves eliminating parameters or neurons within a NN, which have an insignificant contribution to the NN’s functioning [18]. Thus, the pruning helps to reduce the computational complexity and model size, as it decreases the number of operations [16], [17], and we can do this without a noticeable effect on the NN’s performance. Moreover, retraining an already-pruned NN can help to escape local loss-function minima, which can lead to a better functioning accuracy [17]. There are two main types of pruning: static and dynamic. In the static case, the elements are to be removed from the NN after the training but before the inference. In the second case, the pruning takes place during the training stage [17]. In this work, we use the static pruning variant because of its simplicity and chose the NN weights as the elements to be removed.

The static pruning is generally carried out in three steps. Firstly, the parameters to prune are selected, e.g., the weights, the neurons, or both of them. There is no obvious way of choosing which element should be pruned. A simple approach can be just to evaluate the NN’s performance with and without the particular elements. However, this obviously poses scalability problems: we have to evaluate the performance when pruning each particular NN’s parameter, and we can have millions of those. Alternatively, it was also proposed to select the elements to be removed randomly [19]–[21], which can be done faster. Thus, in the current paper, we use the random pruning method.

Secondly, the pruning criterion needs to be defined. As mentioned previously, some rule has to be used for establishing
which elements will be removed from the NN, achieving high levels of sparsity without a significant loss in performance. Regarding the weights pruning criteria, we can remove them based on their magnitude, the NN’s performance penalty, and recurrences [19], [21]. In this work, the weights are pruned depending on their magnitude and sparsity, and the NN is fine-tuned afterward. In Fig. 2 we show the impact when we pruned our NN equalizers in 40%. When comparing the weight distribution of the original model and the pruned one, it is clear that the sparsity level defines the number of weights that need to be pruned and after starting from the smallest valued weights start to be excluded, since as will be presented in the later section, with such level of pruning no degradation in performance is observed. Finally, a retraining or fine-tuning phase (one epoch) is carried out [17] to avoid performance loss.

Fig. 2: Weight distribution of the NN-based equalizers without pruning and with pruning when sparsity is set to be 40%.

Besides the reduction in the number of operations involved in the NN processing, the precision of such arithmetic operations is another crucial factor determining the model’s complexity and memory requirements [22], [23]. Therefore, in addition to pruning, we will change (reduce) the weights’ quantization to further decrease the computational complexity of the equalizer.

Quantization is the process of approximating a continuous variable with a specified set of discrete values, which allows us to reduce memory usage and complexity by lowering the precision of an operation. The number of discrete values will determine the number of bits necessary to represent the data. A NN usually makes use of 32-bit floating-point numbers (FP32). In this case, converting FP32 weights or activation functions to lower bit representations like an 8-bit integer (INT8) can potentially bring down the number of required bits by a factor of 4 leading to a significant cut in memory and computation resources [15]–[17]. The quantization process can take place after training or during it. In the first case, a trained model has its weights, activation quantified to a lower precision and then a fine-tuning step takes place, which means retraining a previously trained model in order to recover the accuracy [16]. In the second case, the training is carried out using low precision values during the forward propagation, while the backward pass remains unchanged. Thus, the quantization error is considered when training the model, making it more robust to quantization [16]. In both cases the parameters are converted to a lower precision data-type, typically INT8 [15]–[17].

In this work, the quantization is carried out after the training stage in addition to a fine-tuning process from FP32 to INT8. Thus, we present here the design of a compressed NN-based channel equalizer, demonstrating that it is possible to achieve a good balance between the performance of the model and its hardware requirements. Additionally, for the first time, we presented that with those compression techniques such NN-based equalizers can be deployed on resource-constrained hardware by running the inference of the model in a Raspberry Pi 4. Finally, it is important to present how can we properly evaluate the computational complexity of such models. In this regard, we quantitatively evaluate the reduction of computation complexity achieved by applying pruning and quantization, calculating the number of bits used during an inference step. The most common operations in a NN are multiply-and-accumulate operations (MACs). These are operations of the form $a = a + w \cdot x$, where three terms are involved, firstly $x$ corresponds to the input signal of the neuron, secondly $w$ refers to the weight, and finally the accumulate variable $a$ [24]. Traditionally, the network complexity arithmetic has been measured using the number of MAC operations. Nevertheless, in the case of this work, the number of bit operations (BoPs) is a more appropriate metric to describe the computational complexity of the model [15], [25], as different data types for the network weights and activations are used.

Considering the effect of unstructured pruning, BoPs in a pruned fully-connected layer can be defined as: $BoPs_i = m_i n_i [1 - f_{pi}] b_w b_i + b_w + \log_2 (n_i)$, where $b_w$ and $b_i$ are the bit width of the weights and activations of the $i$th layer, $n_i$ and $m_i$ the number of inputs and outputs, $f_{pi}$
the fraction of pruned layer weights and for this example \( i \in [1, 2, 3] \). Therefore, the arithmetic complexity of the model is 
\[
BoPs = \sum_i BoPs_i.
\]
It is worth noticing, that the tool used in this work to carry out pruning is the Model Optimisation API provided by Tensorflow [26] and that the pruning is carried out in a uniform way, that is, equal \( f_p \), for \( i \in [1, 2, 3] \).

\[
BoPs_{MLP} = (n_1 n_1 b_1 + n_1 n_2 b_a + n_2 n_3 b_a + n_3 n_o b_a)(1 - f_p) b_w.
\]

Taking into account the above definition of the BoPs metric, it can be seen that there is a reduction in multiplication operations because of pruning. Moreover, BoPs are quadratically dependent on the bit widths and linearly dependent on the pruning fraction. Therefore, quantization will have a bigger influence than pruning when trying to reduce the complexity of the model.

III. COMMUNICATION SYSTEM EQUALIZER DESIGN

In this paper, an MLP NN post-equalizer [6], [8] is implemented to compensate for the nonlinearity-induced impairments in a coherent optical communication system. We analyze the equalizer’s performance in terms of the achieved Q-factor using the simulations data for the 0.1 RRC dual-polarization, 30 Gbd, 64-QAM over 20×50 km links of standard single-mode fiber (SSMF). We have used the same simulator described in [6], [27], to generate our training and testing dataset, and the same procedure of training the NN-based equalizer. The NN is placed at the Rx side after the DSP block, see Fig. 1. The results for three launch powers are analyzed: 0 dBm, 1 dBm, and 2 dBm.

The hyperparameters that define the structure of the NN are obtained using a Bayesian optimizer [6]. The resulting optimized MLP has three hidden layers, with 500, 10, and 500 neurons, respectively, with tanh activation functions and no bias. We used in this paper 10 taps. The NN is subjected to pruning and quantization once properly trained and tested. We analyze the performance of different NN models depending on their sparsity level ranging from 20% to 90% with 10% steps. The weights are quantized converting their data type from FTP32 to INT8. This was done to enable a real-time use of the model deployed on hardware restricted by storage and complexity, such as a Raspberry Pi. The final system is described schematically in Fig. 1. The inference process was carried out using two types of hardware, a computer (PC) with an MSI GP76 Leopard, equipped with an Intel® Core™ i9-10870H, 32GB of RAM as well as a GPU Nvidia RTX2070, and a Raspberry Pi 4 (RB) consisting of an ARM Cortex-A72 and 8 GB of RAM.

IV. RESULTS AND DISCUSSION

In Fig. 3 the Q-factor achieved by the NN equalizer is depicted versus different values of sparsity, for three different launch powers (0 dBm, blue; 1 dBm, red; and 2 dBm, black), for the two types of hardware mentioned above, corresponding the circle marks to the PC (NN in PC) and the squares to the Raspberry Pi (NN in RB). For each of these launch powers, two baselines for the Q-factor are depicted: one corresponds to the level achieved by the unpruned and unquantized NN model (NN), defined by straight lines, while the other gives the benchmark when we do not employ any NN equalization (DSP) and is defined by dotted lines. As it can be seen, the Q-factor value does not change when carrying out the inference in a Raspberry. Moreover, the quantization and pruning process does not cause a significant performance degradation until the 60% of sparsity is reached, where at most 4% performance reduction takes place. Meanwhile, it is necessary to reach sparsity levels of around 90% so that the performance is close to the one achieved without using a NN. Nevertheless, a 20% sparsity is enough for the model to be deployed in resource-constrained hardware as for example the Raspberry Pi when quantization is also applied.

Figure 4 depicts the reduction in the size of the model as well as the model computational complexity for different sparsity values – the consequence of pruning and quantizing the NN. Overall, we have achieved a 95.7% NN memory size reduction after pruning 60% of the NN equalizer weights and quantizing the remaining ones. This emerged into our passing from a memory size of 599.6 down to 25.9 kbits. With respect to the reduction of the computational complexity of the model, using quantization and 60% pruning the computational complexity decreased from 54272000 down to 4582400 BoPs. This way, we achieved a 91.5% reduction in the model computational complexity with pruning 60% of the weights and altering the data type of the remaining weights from FTP32 to INT8. Note once more that, when using sparsity of up to 60% results in no substantial performance loss. Therefore, the same performance can be achieved with a model that is significantly less complex.

Another worth mentioning point is the individual influence that quantization and pruning have on the computational complexity of the model. If the computational complexity is calculated for a quantized but unpruned model, the BoPs value obtained is equal to 11456000. Therefore, if this value is compared with the already mentioned 54272000 BoPs for the unpruned and unquantized NN, a reduction in complexity of a 78.8% is obtained thanks to quantization. As it can be seen
in [4], the remaining gain will come from the pruning technique and it will grow linearly as indicated in Eq. [1].

![Graph showing complexity and size reduction](image)

**Fig. 4:** Complexity and size reduction achieved thanks to pruning and quantization for different levels of sparsity.

Finally, when contrasted to classic mitigation strategies such as digital backpropagation (DBP), it is critical to emphasize the importance of such compression techniques. The Q-factor after DBP utilizing 1, 2, and 3 steps per span (STpS) and their BoPs utilizing 32 float are: i) 8.47 dB and 1712947 BoPs; ii) 9.47 dB and 3343474 BoPs; iii) 9.8 dB and 4975449 BoPs for the case of 0 dBm. To beat the DBP 1STpS, we require an 86% sparsity, a 75% sparsity for the DBP 2 STpS, and a 60% sparsity for the DBP 3 STpS when the CDC and the NN equalizer are combined. Despite the fact that the MLP equalizer could not outperform the DBP performance in the tested scenario, we could observe that it still produces about 0.5 dB gain in the 2dBm case being less complex than the DBP 1 STpS.

**V. CONCLUSION**

We investigated the feasibility of the application of pruning and quantization to reduce the complexity of hardware implementation of an NN-based channel equalizer. We experimentally demonstrated the implementation of the designed equalizer using a Raspberry Pi. It was demonstrated that it is possible to reduce the memory usage by 95.7% and its computational complexity by 91.5% without any major penalty in performance, measured through the Q-factor after inference on the Raspberry Pi, compared to the original equalizer running in a traditional PC.

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