

# POSTER: Efficient All-reduce for Distributed DNN Training in Optical Interconnect Systems

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## Abstract

All-reduce is the crucial communication primitive to reduce model parameters in distributed Deep Neural Networks (DNN) training. Most existing all-reduce algorithms are designed for traditional electrical interconnect systems, which cannot meet the communication requirements for distributed training of large DNNs due to the low data bandwidth of the electrical interconnect systems. One of the promising alternatives for electrical interconnect is optical interconnect, which can provide high bandwidth, low transmission delay, and low power cost. We propose an efficient scheme called WRHT (Wavelength Reused Hierarchical Tree) for implementing all-reduce operation in optical interconnect systems. WRHT can take advantage of WDM (Wavelength Division Multiplexing) to reduce the communication time of distributed data-parallel DNN training. Simulations using real DNN models show that, compared to all-reduce algorithms in the electrical and optical network systems, our approach reduces communication time by 75.76% and 91.86%, respectively.

**CCS Concepts:** • Computing methodologies → Parallel algorithms; Distributed artificial intelligence.

**Keywords:** Optical interconnects, distributed DNN training, all-reduce, WDM

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## 1 Introduction

Data parallelism is one of the most widely adopted paradigms where each worker trains the DNN using its local dataset

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and exchanges model parameters (e.g., gradients) with other workers iteratively [1]. Stochastic Gradient Descent (SGD), the most widespread method for DNN training, intensively invokes data communications for all-reduce operations in distributed deep learning (DL) [2]. All-reduce aims to make every worker receive the model parameters from all the other workers and then apply the reduction operation to get the averaged model parameters. It has been shown that the communications for all-reduce with a large number of workers may occupy 50-90% of per-iteration training time in current traditional electrical networks [3]. The communication time in traditional electrical interconnect can be severely high due to the low bandwidth of electrical routers, high latency of electrical networking, and network congestion. When the overhead caused by communication exceeds the gain brought by the parallel computation, the training performance will be degraded. With the recent development of CMOS-compatible optical devices [4], optical intra/inter-chip network connection is a promising alternative, which can provide high bandwidth, low transmission delay, and low power cost. Moreover, optical interconnect can transmit data through a waveguide using different wavelengths enabled by leveraging WDM, enabling parallel data transmission.

However, most existing all-reduce algorithms are not designed for optical interconnects. They are designed for electrical interconnect systems and do not take advantage of optical features such as parallel data transmission with WDM. For instance, the well-known Ring all-reduce algorithm takes  $2(n-1)$  steps to finish the all-reduce communications [5], where  $n$  is the number of workers. However, such a method is unsuitable for optical interconnect systems because it only assumes one wavelength for transmission in each step, failing to take advantage of the WDM of optical interconnect. Therefore, we propose an efficient all-reduce scheme named WRHT in an optical ring interconnect system with the objective of minimizing the number of communication steps and communication time for the all-reduce operation. As far as we know, WRHT is the first scheme for optimizing all-reduce in optical interconnect systems.

## 2 The WRHT Scheme

WRHT scheme is based on micro-ring resonator optical interconnect architecture called TeraRack [6]. We assume  $N$  computing nodes are connecting with each other sequentially into a ring, and the computing node is GPU. The number

of available wavelengths per waveguide is  $w$ , and the bandwidth per wavelength is  $B$ . We use Figure 1 to illustrate the mechanism of WRHT, which consists of two stages: reduce stage and broadcast stage.

**Reduce stage:** In step 1, all nodes are partitioned into groups along the ring with each group having  $m$  nodes. The intermediate node of each group is selected as the representative node and responsible for collecting the data within each group by  $\lfloor m/2 \rfloor$  wavelengths. After that, each representative node executes a reduction operation to be transmitted in the next step. In the subsequent step  $i$ , the old representative nodes selected in the previous step are further partitioned into  $\lceil \frac{N}{m^i} \rceil$  groups and the middle node of each group is selected as the new representative node as illustrated in Figure 1. This process is repeated until the wavelength is sufficient enough to provide all-to-all communication among the representative nodes in the last step, as illustrated by the dotted box in the middle of Figure 1.

**Broadcast stage:** Once the representative node(s) in the final step of reduce stage obtain the final reduction value, the process of broadcast stage is the reverse of reduce stage. Specifically, the representative nodes broadcast the reduction data in corresponding groups using  $\lfloor m/2 \rfloor$  wavelengths, which is repeated according to the hierarchical tree structure until all the nodes receive the reduce data, as illustrated in the lower part of Figure 3. As a result, the total number of communication steps for WRHT is  $2\lceil \log_m N \rceil$  or  $2\lceil \log_m N \rceil - 1$ .

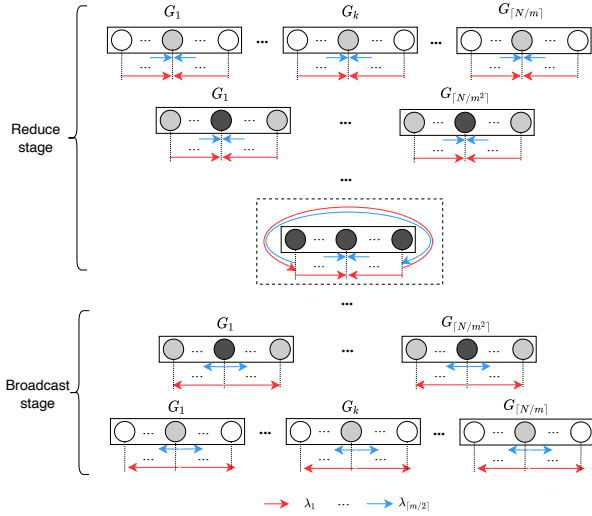


Figure 1. The working principle in WRHT scheme

Since nodes are partitioned into subgroups in each step by WRHT, communications within each subgroup need to be assigned with proper wavelengths to avoid conflicts, while communications from different subgroups do not share any link between groups on the ring topology. Therefore, we can use wavelength assignment approach First Fit [7] or Best Fit [8] for assigning the wavelengths within each subgroup.

As the number of nodes in each subgroup is  $m$  and the intermediate node is selected as the representative node, it is easy to derive that the wavelength requirement is  $\lfloor m/2 \rfloor$ . For the last step in reduce stage, the number of representative nodes can be derived as  $m^* = \lceil \frac{N}{m^{\lceil \log_m N \rceil - 1}} \rceil$ , which requires  $\lceil \frac{(m^*)^2}{8} \rceil$  wavelengths for all-to-all communications [9] when  $m^* > 1$ .

### 3 Experimental Setup and Results

DNN models used in the simulation are AlexNet (62.3M parameters) [10], VGG16 (138M parameters) [11], ResNet50 (25M parameters) [12] and GoogLeNet (6.7977M parameters) [13] with ImageNet dataset [14]. We implement WRHT along with a list of all-reduce algorithms in our optical interconnect simulator, and we use SimGrid [15] to simulate the electrical network system. We estimate the communication time by numerically setting different transferred data of DNNs, number of nodes, wavelengths, etc. in our simulator and SimGrid.

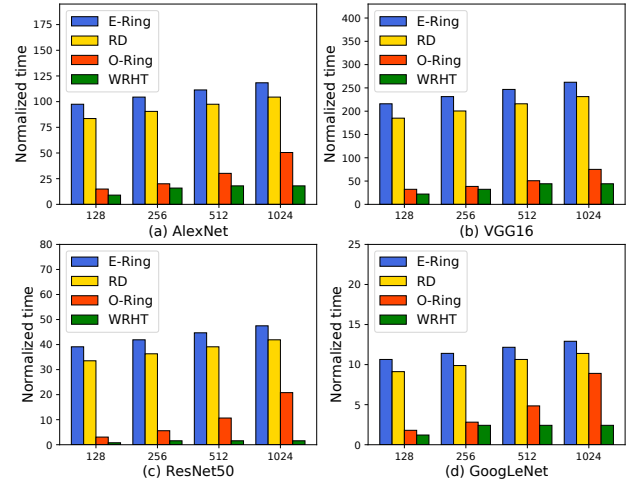


Figure 2. The comparison of communication time in electrical interconnect and optical interconnect system using different all-reduce algorithms

Figure 2 compares the communication time of Ring and RD all-reduce algorithms in electrical interconnect system with Ring all-reduce and WRHT in the optical interconnect system by different DNN models across different scales.

### 4 Conclusion

In this paper, we propose an efficient all-reduce algorithm in optical interconnect systems called WRHT by taking advantage of the multiple wavelengths to reduce the total number of communication steps. We have shown that our method significantly outperforms the all-reduce algorithms in electrical and optical interconnect systems with 75.76% and 91.86% communication time reduction.

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