

# Intra-DP: A High Performance Distributed Inference System on Robotic IoT

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## Abstract

The rapid advancements in machine learning (ML) techniques have led to significant achievements in various robotic tasks, where deploying these ML approaches on real-world robots requires fast and energy-efficient inference of their deep neural network (DNN) models. Distributed inference, which involves inference across multiple powerful GPU devices, has emerged as a promising optimization to improve inference performance in modern data centers. However, when deployed over Internet of Things of these real-world robots (robotic IoT), all existing parallel methods (data parallelism, tensor parallelism, pipeline parallelism) fail to simultaneously meet the robots' latency and energy requirements and raise significant challenges due to the failure of data parallelism, the unacceptable communication overhead of tensor parallelism, and the significant transmission bottlenecks in pipeline parallelism due to the limited bandwidth of robotic IoT.

We present Intra-DP, the first high-performance distributed inference system optimized for model inference on robotic IoT. Intra-DP introduces a fine-grained approach to transmission and computation by confining them to each local operator of DNN layers (i.e., operators that can be computed independently without the complete input, such as the convolution kernel in the convolution layer). By adaptively scheduling the computation and transmission of each local operator based on various hardware conditions and network bandwidth, Intra-DP enables different local operators of different layers to be computed and transmitted concurrently, and overlap the computation and transmission phases within the same inference task to achieve fast and energy-efficient distributed inference on robotic IoT. The evaluation shows that Intra-DP reduces inference time by 20% and energy consumption by 10% compared to the state-of-the-art baselines.

**Keywords:** Distributed inference, Robotic IoT, Distributed system and network

## 1 Introduction

The rapid progress in machine learning (ML) techniques has led to remarkable achievements in various fundamental robotic tasks, such as object detection [20, 30, 33], robotic control [24, 50, 60], and environmental perception [4, 25, 55]. However, deploying these ML applications on real-world robots requires fast and energy-efficient inference of their deep neural network (DNN) models, given the need for swift

environmental responses and the limited battery capacity of robots. Placing the entire model on robots not only requires additional computing accelerators on robots (e.g., GPU [37], FPGA [38], SoC [16]), but also introduce additional energy consumption (e.g., 162% more for [33] in our experiments) due to the computationally intensive nature of DNN models, while placing the entire model in the cloud brings an extended response delay.

Distributed inference, which involves inference across multiple GPU devices, has emerged as a promising approach to meet the latency requirements of robotic applications and extend the battery lifetime of robots. This paradigm has been widely adopted in data centers [18, 56, 64], where numerous GPUs are utilized to speed large model inference, such as in the case of ChatGPT [54]. Adopting distributed inference across robots and other powerful GPU devices through the Internet of Things for these robots (robotic IoT) not only accelerates the inference process by leveraging the high computing capabilities of powerful GPUs but also alleviates the local computational burden, thereby reducing energy consumption, making it an ideal solution for robotic applications.

However, all existing parallel methods for distributed inference in the data center are ill-suited for robotic IoT. In data centers, there are mainly three kinds of parallel methods: Data parallelism (DP) replicates the model across devices, and lets each replica handle one mini-batch (i.e., a subset that slices out of an input data set); Tensor parallelism (TP) splits a single DNN layer over devices; Pipeline parallelism (PP) places different layers of a DNN model over devices (layer partitioning) and pipelines the inference to reduce devices' idling time (pipeline execution).

For DP, the small batch sizes inherent to robotic IoT applications (typically 1) hinder the mini-batch computation, rendering DP inapplicable for robotic IoT. In the data center, DP is feasible due to the large batch sizes employed (e.g., 16 images), allowing for the division of inputs into mini-batches that still contain several complete inputs (e.g., 2 images). However, in robotic IoT, real-time performance is crucial, necessitating immediate inference upon receiving inputs, which typically have smaller batch sizes (e.g., 1 image). Further splitting these inputs would result in mini-batches containing incomplete inputs (e.g., 1/4 of an image), which cannot be computed parallel to speed up inference.

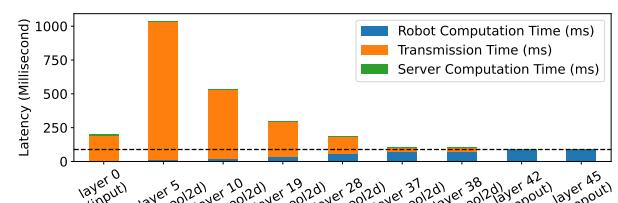
TP requires frequent synchronization among devices, leading to unacceptable communication overhead in robotic IoT.

111 By partitioning parameter tensors of a layer across GPUs,  
 112 TP allows concurrent computation on different parts of this  
 113 tensor but requires an all-reduce communication [64] to  
 114 combine computation results from different devices, which  
 115 entails significant communication overhead. Consequently,  
 116 TP is used mainly for large layers that are too large to fit in  
 117 one device in data centers and require dedicated high-speed  
 118 interconnects (e.g., 400 Gbps for NVLink [23]) even within  
 119 data centers. On the contrary, robots must prioritize seam-  
 120 less mobility and primarily depend on wireless connections,  
 121 which inherently possess limited bandwidth, as described in  
 122 Sec. 2.1, making all-reduce synchronization an unacceptable  
 123 overhead (e.g., the inference time with TP was up to 143.9X  
 124 slower than local computation in Sec.2.3.).

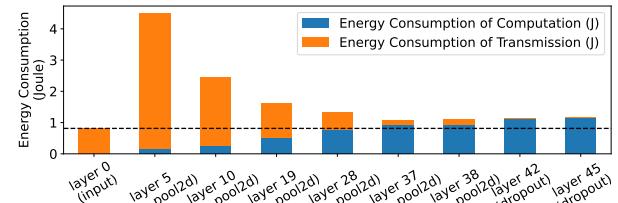
125 Consequently, existing distributed inference approaches [5,  
 126 26] in robotic IoT primarily adopt the PP paradigm and fo-  
 127 cus on layer partitioning of PP, aiming to achieve fast and  
 128 energy-efficient inference. This is because the PP paradigm  
 129 in data centers consists of layer partitioning and pipeline  
 130 execution, where the pipeline execution of PP enhances infer-  
 131 ence throughput rather than reducing the completion time of  
 132 a single inference [6], which is the most critical requirement  
 133 in robotic IoT. Based on the fact that the amounts of output  
 134 data in some intermediate layers of a DNN model are sig-  
 135 nificantly smaller than that of its raw input data [17], DNN  
 136 layer partitioning strategies constitute various trade-offs be-  
 137 tween computation and transmission, taking into account  
 138 application-specific inference speed requirements and en-  
 139 ergy consumption demands, as shown in Fig. 1.

140 However, existing methods based on PP face significant  
 141 transmission bottlenecks in robotic IoT due to the inherent  
 142 scheduling mechanism. PP paradigm on robotic IoT consists  
 143 of three sequential phases: computing earlier DNN layers on  
 144 robots, transmitting intermediate results, and completing in-  
 145 ference on the GPU server. Despite optimal layer partitioning  
 146 strategies from [5, 26], the transmission overhead becomes  
 147 a substantial bottleneck due to limited bandwidth of robotic  
 148 IoT, accounting for up to 69% of inference time in our ex-  
 149 periments. While the pipeline execution of PP can mitigate  
 150 this overhead by overlapping computation and transmis-  
 151 sion phases across multiple inference tasks, it cannot reduce  
 152 the completion time of a single inference task [6], which is  
 153 crucial for robotic applications. Furthermore, the prolonged  
 154 transmission phase not only slows down inference speed but  
 155 also consumes significantly more energy.

156 The key reason for the problem of the above methods is  
 157 that existing methods conduct layer-granulated scheduling,  
 158 whose transmission time is typically longer than the computa-  
 159 tion time due to the limited bandwidth of real-world robotic  
 160 IoT networks. As transmission time constitutes a substantial  
 161 portion of the total inference time (approximately half) in  
 162 existing methods, a novel parallel method with finer gran-  
 163 ularity that overlaps computation and transmission within  
 164 the same inference task has the potential to address this



(a) Inference Latency



(b) Energy consumption on robot

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**Figure 1.** Existing distributed inference approaches on VGG19 [45] in our experiments, which adopt PP paradigm with various layer partitioning scheduling strategies. The X-axis of the graph represents different layer partitioning strategies, where ‘layer i’ indicates that all layers up to and including the i-th layer are computed on the robot, while the subsequent layers are processed on the GPU server.

shortcoming, achieving fast and energy-efficient inferences. Note that the robot can not enter low-power sleep mode during the transmission phase due to the need to promptly continue working upon receiving inference results, but can only enter standby mode, when chips like CPU, GPU, and memory consume non-negligible power even when not computing (e.g., 95% power consumption in our experiments). Such a parallel method would reduce the robot’s standby time without significantly increasing energy consumption during the computation phase, thereby decreasing overall energy consumption.

In this paper, we present Intra-DP (Intra-Data Parallel), a high-performance distributed inference system optimized for real-world robotic IoT networks. We discovered that operators for each DNN layer (e.g., convolution, ReLU, softmax) can be categorized into two types: local operators and global operators, depending on whether they can be computed independently without the complete input. For instance, softmax [31] requires the complete input vector to calculate the corresponding probability distribution, referring to it as a global operator, while ReLU [7] and convolution [34] can be computed with part of the input tensor (the elements in the input vector for ReLU and the blocks in the input tensor

for convolution), referring to them as local operators. Local operators need to be executed several times to complete the calculation of the whole layer; in this article, we treat each execution of the local operator as an independent local operator for easy discussion. Local operators are widely used in robotic applications, especially convolution layers in computer vision [33] and point cloud tasks [50]. The local operator granularity provides a finer granularity for Intra-DP, allowing different local operators of different layers to be computed and transmitted concurrently, enabling the overlapping of computation and transmission phases within the same inference task to achieve fast and energy-efficient inference.

The design of Intra-DP is confronted with two major challenges. The first one is how to guarantee the correctness of inference results based on local operator. We propose Local Operator Parallelism (LOP), which reduces the granularity of calculation from each layer to each local operator. LOP determines the correct input required for different local operators based on their calculation characteristics and processes at first. When a part of the local operators in a layer completes the calculation and the tensor composed of these local operators satisfies the input requirements of the local operators in the subsequent layer, the local operators in the subsequent layer can be calculated in advance, without waiting for all local operators of the current layer to be computed in LOP. For global operator layers, Intra-DP enforces a synchronization before these layers to combine the complete input for them, as TP's all-reduce communications do. In this way, Intra-DP only change the execution sequence of local operators among local operator layers and ensures the calculation correctness of local operator layers through LOP and global operator layers through synchronization. We formally prove that LOP guarantees the correctness of inference results in Sec. 4.1.

The second challenge is under LOP, how to properly schedule the computation and transmission of each local operator to achieve fast and energy-efficient inference under various hardware conditions and network bandwidths. Intra-DP places part of the local operator execution on GPU servers and transmits the corresponding part of the input tensor based on LOP, while computing the rest of the local operators with a novel Local Operator Scheduling Strategy (LOSS). LOSS formulates the problem of determining which part of the local operators should be executed on robots and which part should be executed on GPU servers as a nonlinear optimization problem (see Sec. 4.2), and schedules the computation and transmission of each local operator based on the solution obtained via the differential evolution algorithm [42].

We implemented Intra-DP in PyTorch [40] and evaluated Intra-DP on our real-world robots under two typical real-world robotic applications [33, 50] and several models common to mobile devices on a larger scale [45, 46, 48, 52, 57].

We compared Intra-DP with two SOTA pipeline parallelism methods as baselines: DSCCS [26], aimed at accelerating inference, and SPSO-GA [5], focused on optimizing energy consumption, under different real-world robotic IoT networks environments (namely indoors and outdoors). Evaluation shows that:

- Intra-DP is fast. Intra-DP reduced inference time by 80% ~98% compared to baselines under indoors and outdoors environments.
- Intra-DP is energy-efficient. Intra-DP reduced 91% ~98% energy consumption per inference compared to baselines, due to faster inference speed and no-increased power consumption against time.
- Intra-DP is robust in various robotic IoT environments. When the robotic IoT environment changed (from indoors to outdoors), Intra-DP's superior performance remained consistent.
- Intra-DP is easy to use. It took only three lines of code to apply Intra-DP to existing ML applications.

Our main contribution are LOP, a fine-grained parallel method based on local operators, and LOSS, a new scheduling strategy based on LOP optimized for distributed inference over real-world robotic IoT networks. By leveraging these contributions, Intra-DP dramatically reduces the transmission overhead in existing distributed inference on robotic IoT by overlapping the computation and transmission phases within the same inference task, achieving fast and energy-efficient distributed inference on robotic IoT. We envision that the fast and energy-efficient inference of Intra-DP will foster the deployment of diverse robotic tasks on real-world robots in the field. Intra-DP's code is released on <https://github.com/xxx/xxx>.

In the rest of this paper, we introduce the background of this paper in Sec. 2, give an overview of Intra-DP in Sec. 3, present the detailed design of Intra-DP in Sec. 4, evaluate Intra-DP in Sec. 6, and finally conclude in Sec. 7.

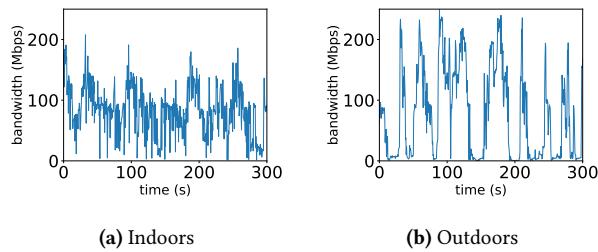
## 2 background

### 2.1 Characteristics of Robotic IoT

In real-world robotic IoT scenarios, devices often navigate and move around for tasks like search and exploration. While wireless networks provide high mobility, they also have limited bandwidth. For instance, Wi-Fi 6, the most advanced Wi-Fi technology, offers a maximum theoretical bandwidth of 1.2 Gbps for a single stream [29]. However, not only the limited hardware resources on the robot can not fully play the potential of Wi-Fi 6 [59], but also the actual available bandwidth of wireless networks is often reduced in practice due to factors such as movement of the devices [32, 39], occlusion from by physical barriers [9, 44], and preemption of the wireless channel by other devices [2, 43].

To demonstrate the instability of wireless transmission in real-world situations, we conducted a robot surveillance

331 experiment using four-wheel robots navigating around several given points at 5-40cm/s speed in our lab (indoors) and  
 332 campus garden (outdoors), with hardware and wireless net-  
 333 work settings as described in Sec. 6. We believe our setup  
 334 represents robotic IoT devices’ state-of-the-art computation  
 335 and communication capabilities. We saturated the wireless  
 336 network connection with iperf [1] and recorded the average  
 337 bandwidth capacity between these robots every 0.1s for 5  
 338 minutes.  
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**Figure 2.** The instability of wireless transmission in robotic  
 348 IoT networks.  
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350 The results in Fig. 2 show average bandwidth capacities  
 351 of 93 Mbps and 73 Mbps for indoor and outdoor scenarios,  
 352 respectively. The outdoor environment exhibited higher in-  
 353 stability, with bandwidth frequently dropping to extremely  
 354 low values around 0 Mbps, due to the lack of walls to reflect  
 355 wireless signals and the presence of obstacles like trees be-  
 356 tween communicating robots, resulting in fewer received  
 357 signals compared to indoor environments.  
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359 In summary, robotic IoT systems’ wireless transmission  
 360 is constrained by limited bandwidth, both due to the theo-  
 361 retical upper limit of wireless transmission technologies and  
 362 the practical instability of wireless networks. Moreover, the  
 363 unstable bandwidth in robotic IoT wireless networks can  
 364 cause the transmission time to vary dramatically, sometimes  
 365 changing by hundreds of times. In our experiments, even  
 366 a relatively small model with only 0.84M parameters still  
 367 suffers from its significant transmission overhead.  
 368

## 369 2.2 Characteristics of Data Center Networks

370 Data center networks, which are used for large model in-  
 371 ference (e.g., ChatGPT [54]), are wired and typically exhibit  
 372 higher bandwidth capacity and lower fluctuation compared  
 373 to robotic IoT networks. GPU devices in data centers are  
 374 interconnected using high-speed networking technologies  
 375 such as InfiniBand [49] or PCIe [23], offering bandwidths  
 376 ranging from 40 Gbps to 500 Gbps. The primary cause of  
 377 bandwidth fluctuation in these networks is congestion on  
 378 intermediate switches, which can be mitigated through traf-  
 379 fic scheduling techniques implemented on the switches [36].  
 380 The stable and high-bandwidth nature of data center net-  
 381 works makes them well-suited for demanding tasks like  
 382

383 large model inference, in contrast to the more variable and  
 384 resource-constrained environments found in robotic IoT net-  
 385 works.  
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## 387 2.3 Existing distributed inference methods in the 388 data center

389 **Data parallelism.** Data parallelism [56] is a widely used  
 390 technique in distributed inference that partitions input data  
 391 across multiple devices, such as GPUs, to perform parallel  
 392 inference. Each device maintains a complete model replica  
 393 and independently processes a subset of the input data (mini-  
 394 batch), aggregating results to generate the final output. Data  
 395 parallelism enhances throughput by distributing workload  
 396 across devices, leveraging their combined computational  
 397 power.  
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399 However, data parallelism’s scalability is constrained by  
 400 the total batch size [35], which is particularly problematic  
 401 in robotic IoT applications where smaller batch sizes are  
 402 inherent due to the need for swift environmental responses.  
 403 In robotic applications, immediate inference upon receiving  
 404 inputs is crucial for obtaining real-time target points quickly.  
 405 For example, in our experiments, the robot constantly obtains  
 406 the latest images from the camera for inference, with a batch  
 407 size of only 1. These small batches cannot be further split  
 408 into mini-batches, a fundamental requirement for effective  
 409 data parallelism.  
 410

411 **Tensor parallelism.** Tensor parallelism [64] is a dis-  
 412 tributed inference technique that divides a model’s layer  
 413 parameters across multiple devices, each storing and com-  
 414 puting a portion of the weights. This approach requires an  
 415 all-reduce communication step after each layer to combine  
 416 results from different devices, introducing significant over-  
 417 head, especially for large DNN layers. To mitigate this, TP is  
 418 typically deployed across GPUs within the same server in  
 419 data centers, using fast intra-server GPU-to-GPU links like  
 420 NVLink [23], which is beneficial when the model is too large  
 421 for a single device.  
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423 In contrast to data center networks, the limited bandwidth  
 424 in robotic IoT renders the communication cost of TP prohib-  
 425 itively high, as evidenced by our evaluation of DINA [34],  
 426 a state-of-the-art TP method. Table 1 reveals that transmis-  
 427 sion time constitutes 49% to 94% of the total inference time  
 428 due to all-reduce communication for each layer, resulting  
 429 in TP’s inference time being 45.2X to 143.9X longer than  
 430 local computation. Although Table 2 indicates lower power  
 431 consumption with TP (13.4% to 67.3% less than local computa-  
 432 tion), the extended transmission times significantly increase  
 433 energy consumption per inference, ranging from 28.5X to  
 434 62.7X. Since TP significantly extends inference time, making  
 435 it impractical for real-world robotic applications, we did not  
 436 further consider TP in this paper.  
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438 **Pipeline parallelism.** Pipeline parallelism [18] is a dis-  
 439 tributed inference technique that partitions DNN model  
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Model(number of parameters)	Local computation time(s)	Environment	Transmission time (s) with TP	Inference time (s) with TP	Percentage(%) with TP
MobileNet_V3_Small(2M)	0.031( $\pm 0.004$ )	indoors outdoors	0.698( $\pm 0.135$ ) 0.901( $\pm 0.778$ )	1.400( $\pm 0.232$ ) 1.775( $\pm 1.370$ )	49.85 51.23
ResNet101(44M)	0.065( $\pm 0.005$ )	indoors outdoors	7.156( $\pm 3.348$ ) 8.470( $\pm 6.337$ )	8.106( $\pm 3.403$ ) 9.356( $\pm 6.328$ )	87.95 90.46
VGG19_BN(143M)	0.063( $\pm 0.002$ )	indoors outdoors	5.152( $\pm 4.873$ ) 5.407( $\pm 6.673$ )	5.444( $\pm 4.831$ ) 5.759( $\pm 6.635$ )	70.18 93.70

**Table 1.** Average transmission time (Second), inference time (Second), percentage that transmission time accounts for of inference time and their standard deviation ( $\pm n$ ) with TP on different models in different environments. “Local computation” refers to placing the whole layers on the robot.

Model(number of parameters)	Environment	Power consumption(W)		Energy consumption(J) per inference	
		Local	TP	Local	TP
MobileNet_V3_Small(2M)	indoors outdoors	6.05( $\pm 0.21$ ) 6.05( $\pm 0.21$ )	5.24( $\pm 0.19$ ) 5.11( $\pm 0.28$ )	0.3( $\pm 0.09$ ) 0.3( $\pm 0.09$ )	7.33( $\pm 1.21$ ) 9.08( $\pm 7.0$ )
ResNet101(44M)	indoors outdoors	11.27( $\pm 0.51$ ) 11.27( $\pm 0.51$ )	4.97( $\pm 0.16$ ) 4.9( $\pm 0.23$ )	0.93( $\pm 0.19$ ) 0.93( $\pm 0.19$ )	40.28( $\pm 16.91$ ) 45.8( $\pm 30.98$ )
VGG19_BN(143M)	indoors outdoors	14.86( $\pm 0.43$ ) 14.86( $\pm 0.43$ )	4.88( $\pm 0.29$ ) 4.87( $\pm 0.27$ )	1.19( $\pm 0.18$ ) 1.19( $\pm 0.18$ )	26.55( $\pm 23.56$ ) 28.06( $\pm 32.33$ )

**Table 2.** Power consumption against time (Watt) and energy consumption per inference (Joule) with standard deviation ( $\pm n$ ) with TP on different models in different environments. “Local” represents “Local computation”

layers across multiple devices(layer partitioning), forming an inference pipeline for concurrent processing of multiple tasks. While PP can increase throughput and resource utilization via pipeline execution, it primarily focuses on enhancing overall throughput rather than reducing single-inference latency [6], which is crucial in robotic IoT. As a result, existing distributed inference approaches [5, 26] in robotic IoT primarily adopt PP paradigm and focus on layer partitioning to achieve fast and energy-efficient inference, with two main categories based on their optimization goals: accelerating inference for diverse DNN structures [17, 21, 26, 34, 58] and optimizing robot energy consumption during inference [5, 27, 53]. Both two kinds of methods suffer from the transmission bottleneck inherent to PP’s scheduling mechanism, which can be eliminated by Intra-DP.

## 2.4 Other methods to speed up DNN Models

### Inference on Robotic IoT

**Compressed communication.** Compressed communication is crucial for efficient distributed inference in wireless networks, as it significantly reduces communication overhead through techniques such as quantization and model distillation. Quantization [8, 13, 14] is a technique that reduces the numerical precision of model weights and activations, thereby minimizing the memory footprint and

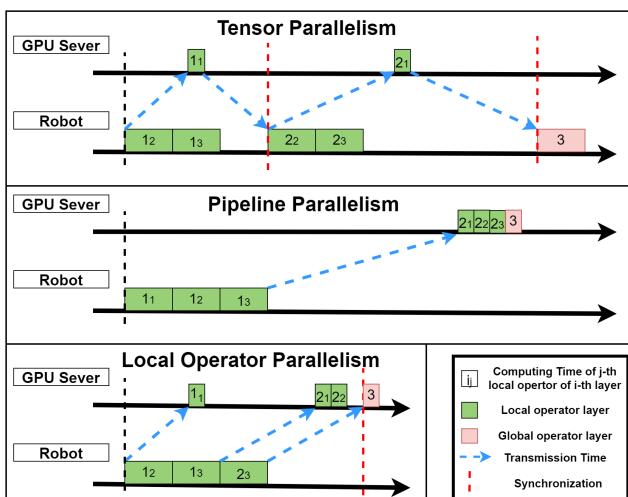
computational requirements of deep learning models. This process typically involves converting high-precision (e.g., 32-bit) floating-point values to lower-precision (e.g., 8-bit) floating-point representations, with minimal loss of model accuracy. Model distillation [15, 28, 51], on the other hand, is an approach that involves training a smaller, more efficient “student” model to mimic the behavior of a larger, more accurate “teacher” model by minimizing the difference between the student model’s output and the teacher model’s output. The distilled student model retains much of the teacher model’s accuracy while requiring significantly fewer resources. These model compression methods complement distributed inference by achieving faster inference speed through model modifications, potentially sacrificing some accuracy with smaller models, while distributed inference realizes fast inference without loss of accuracy by intelligently scheduling computation tasks across multiple devices.

**Inference Job scheduling.** Significant research efforts have been devoted to exploring inference parallelism and unleashing the potential of layer partition to accelerate DNN inference, such as inference job scheduling, aiming to accelerate multiple DNN inference tasks by optimizing their execution on various devices under different network bandwidths while considering application-specific inference speed requirements and energy consumption demands. For instance, [3,

[551] support online scheduling of offloading inference tasks  
 [552] based on the current network and resource status of mobile  
 [553] systems while meeting user-defined energy constraints. [11]  
 [554] focused on optimizing DNN inference workloads in cloud  
 [555] computing using a deep reinforcement learning based sched-  
 [556] ule for QoS-aware scheduling of heterogeneous servers, aim-  
 [557] ing to maximize inference accuracy and minimize response  
 [558] delay. While these methods focus on overall optimization in  
 [559] multi-task scenarios involving multi-robots, they do not ad-  
 [560] dress the optimization of single inference tasks and are thus  
 [561] orthogonal to distributed inference for a single inference,  
 [562] where improved distributed inference can provide faster and  
 [563] more energy-efficient inference for these scenarios.

### 3 Overview

#### 3.1 Workflow of Intra-DP



**Figure 3.** Workflow of Intra-DP. Each local operator layer have to complete the calculation of three local operators, and the same local operator in the three cases has the same computation time on robots and GPU servers, as well as the corresponding transmission time. The output tensor volume of layer 2 is larger than that of layer 1, resulting in longer transmission times for local operators in layer 2, and PP selects a layer partition strategy at layer 1 [26].

Fig. 3 presents the workflow of Intra-DP and compares it with TP and PP under robotic IoT networks with limited bandwidth, illustrating why existing methods suffer from transmission overhead and how Intra-DP solves this issue via its LOP.

While TP can place some local operator execution on the GPU server, it requires an all-reduce communication [64] to combine computation results from different devices, which entails significant communication overhead (as shown by the red dotted lines for synchronization Fig. 3). Although the layer partition algorithm [26] can be used to minimize

overall inference time, the transmission time still becomes a significant bottleneck, as illustrated by the extremely long transmission in Fig. 3.

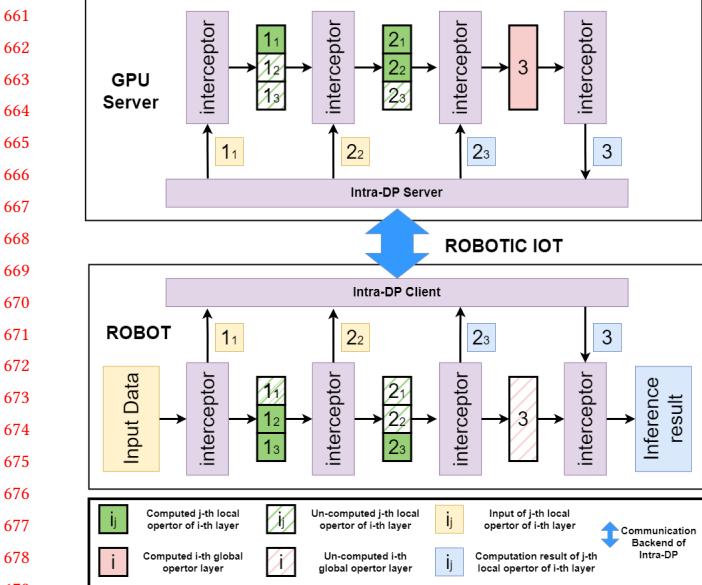
To alleviate the transmission overhead in distributed inference, Intra-DP overlaps the computation and transmission of different local operators from different local operator layers, as shown in Fig. 3. Compared with TP, Intra-DP cancels the synchronization of the all-reduce communication for local operator layers and ensures that each local operator can get the required input in time and obtain the correct calculation results through LOP, rather than relying on all-reduce communication for local operator layers. Intra-DP maintains synchronization for global operator layers, which do not have local operators and require the complete input (the entire output tensor of the previous layer) to perform the calculation, ensuring the correctness of the global operator layers' inference. Compared with PP, Intra-DP starts transmitting some local operators and the corresponding input in advance, without waiting for all local operators in the current local operator layer to complete the calculation. In this way, Intra-DP achieves much faster inference compared with existing distributed inference methods.

Moreover, the idle time on the robot (when the robot is not computing, as shown in Fig. 3) consumes significant energy. This is because the robot cannot enter a low-power sleep mode while waiting for the final inference result from the GPU server, as it has to promptly continue working when it receives the inference results. During the standby phase (idle time), chips like CPU, GPU, and memory consume non-negligible power even when not computing, due to the static power consumption rooted in transistors' leakage current [22]. Meanwhile, we found that wireless network cards consume only 0.21 Watt for transmission during the idle time, while the robot consumes 13.35 Watt during computing. In this way, Intra-DP dramatically reduces the idle time on the robot, alleviating the energy wasted by standby mode, and increases a negligible amount of network card transmission power consumption during computing, thereby reducing the overall energy consumption for each inference.

To achieve the workflow shown in Fig. 3, the design of Intra-DP must tackle two problems: guaranteeing the correctness of inference results based on local operators and scheduling the computation and transmission of each local operator. In Sec.4.1, we will explain how Intra-DP ensures that each local operator can still obtain the correct calculation result via LOP, and in Sec.4.2, we will discuss how Intra-DP achieves fast and energy-efficient inference through its LOSS.

#### 3.2 Architecture of Intra-DP

Fig. 4 shows the architecture of Intra-DP, which adds an interceptor for each DNN layer to flexibly split the input tensor and combine the output tensor for each operator. Compared



**Figure 4.** Architecture of Intra-DP. The core components of Intra-DP are highlighted in purple. Intra-DP adopts the same scheduling scheme as in Fig. 3.

with the original model inference process on the robot, Intra-DP only increases the time cost of interceptors, which is the time cost of splitting the input tensor and combining the output tensor. The time cost of splitting the input tensor is negligible because the data transfer can be completed through the backend processes of the Intra-DP client and server while the local operators assigned to be executed on the robot and GPU server continue to perform subsequent layer calculations. The time cost of combining the output tensor is mainly bound by the time when the device on the other side completes the corresponding computation and transmission, causing prolonged waiting time. Intra-DP formulates such waiting time into the nonlinear optimization problem in its LOSS, minimizing the waiting time and implementing scheduling schemes on local operators with a higher degree of parallelism. In this way, Intra-DP only increases negligible extra time on system cost and achieves faster inference via LOP and LOSS.

To address frequent fluctuations in real-world wireless networks of robotic IoT, Intra-DP generates optimal local operator scheduling strategies for the DNN model under different bandwidth conditions in advance. During inference, Intra-DP predicts the network bandwidth using mature tools [62] in the field of wireless transmission and adopts the corresponding scheduling strategy based on the predicted bandwidth. To ensure that Intra-DP can flexibly switch among various scheduling strategies, it keeps a copy of the model on the robot at the GPU server (Fig. 4), avoiding unnecessary transmission when migrating the parameters of local operators between robots and the GPU server. It is important to note

that the model inference time, typically tens or hundreds of milliseconds, is finer (smaller) than the granularity (or frequency) of bandwidth fluctuation in real-world robotic IoT networks, as shown in Fig. 2. Therefore, we assume that the network bandwidth of robotic IoT during each inference is stable, while the network bandwidth for different inferences may differ.

## 4 Detailed Design

### 4.1 Local Operator Parallelism

LOP guarantees the correctness of inference results by determining the correct input required for different local operators based on their calculation characteristics and processes. We summarize three classes of local operators common in models used on mobile devices:

- Element-wised local operator. This class of operators compute each element of the input tensor separately, requiring only the corresponding element from the input tensor to perform the calculation. They are widely used in activation functions such as ReLU [7], Sigmoid [61], SiLU [19]. However, it is important to note that some activation functions, like softmax [31], require all elements for computation and are not considered local operators, but global operators.
- Block-wised local operator. This class of operators require a block at the corresponding position in the input tensor and are widely used in layers associated with convolution, such as convolution [34], max-pool [47]. The size of the input blocks is determined by the parameters set by the corresponding layer [41], including the size of the convolution kernel, padding, and dilation.
- Row-wised local operator. This class of operators requires rows of the input tensor and are widely used in layers associated with matrix operations, such as addition [63] and multiplication [12]. The rows required for computation, ensuring that the correct input is obtained for each local operator to perform its respective calculation, are determined by the matrix calculation principles as following:

$$\begin{pmatrix} a_1 \\ \vdots \\ a_m \end{pmatrix} \times (b_1 \quad \cdots \quad b_n) = \begin{pmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{m1} & \cdots & c_{mn} \end{pmatrix}$$

Row-wised local operators split the input matrix and keep a copy of the layer parameter matrix on different devices, reducing transmission volume and avoiding the synchronization needed to combine calculation results from different devices. This is in contrast to TP, which splits the layer parameter matrix and transfers a copy of the input matrix to different devices. The calculation result of row  $a_1$  is  $(c_{11} \cdots c_{1n})$ , which is also a row and can be directly computed by the next

771 matrix operation layer. And LOP treats matrices with  
 772 only one row as global operators.

773 After obtaining the required input for each local operator  
 774 and the corresponding input position in the previous layer  
 775 through the above analysis, LOP determines which local  
 776 operators need to be computed in the previous layer to obtain  
 777 the input for the current local operator. This establishes  
 778 the dependency between local operators, which should be  
 779 considered when scheduling local operators as LOSS. And  
 780 we leave the support for additional types of local operators  
 781 as future work.

## 783 4.2 Local Operator Scheduling Strategy

784 LOSS formulates the problem of scheduling local operators  
 785 as a nonlinear optimization problem, which is modeling as  
 786 follows:

787 First of all, we identify the complete time of i-th layer on  
 788 robot on robots as  $T_{robot}^i$  and that on GPU server as  $T_{server}^i$ .

789 Then LOP schedules the computation and transmission of  
 790 each local operator based on the solution obtained via the  
 791 differential evolution algorithm [42].

## 793 4.3 Algorithms of Intra-DP

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### 795 Algorithm 1: Local\_Operator\_Scheduling\_Strategy

796 **Input:** Cuda kernel function called by the corresponding  
 797 operator *func* and the required parameters *args*  
 798 **Output:** The execution result *ret*  
 799 **Data:** inference operator sequence *IOS* = 0  
 800 1 **if** *IOS.empty()* **then**  
 801 | | recorder  
 802 | | *SendRPCtoServer(func, args)*  
 803 | | *IOS = DataDependencySearch(func, args)*  
 804 | | 4 *ret = GetRPCExecutionResult()*  
 805 | | 5 *RecordReturn(ret)*  
 806 6 **end**  
 807 7 **else**  
 808 | | // replayer on robot  
 809 | | 8 **if** *func == IOS.start()["func"]* **then**  
 810 | | | | 9 *ret = StartRRTO(args, IOS)*  
 811 | | | | // start a new inference  
 812 | | 10 **end**  
 813 | | 11 **else if** *func == IOS.end()["func"]* **then**  
 814 | | | | 12 *ret = WaitingForRRTO()*  
 815 | | | | // Waiting for the final computation result  
 816 | | 13 **end**  
 817 | | 14 **else**  
 818 | | | | 15 *ret = IOS.find(func)["ret"]*  
 819 | | 16 **end**  
 820 17 **end**  
 821 18 **return** *ret*

---

	inference	transmission	standby
Power (W)	13.35	4.25	4.04

826 **Table 3.** Power consumption (Watt) of our robot in different  
 827 states.  
 828  
 829  
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 836

## 5 Implementation

Intra-DP is easy to use and requires only three lines of code to apply to existing ML applications, as shown in Fig. 5.

```
837 163 # Other part of pytorch as usual
838 164
839 165 # Import package of Intra-DP
840 166 import intraDP
841 167
842 168 # Define a VGG19 model as usual
843 169 vgg19 = VGG19().to(device)
844 170
845 171 # Apply Intra-DP
846 172 IDP = intraDP(ip = "192.168.50.1")
847 173 IDP.start_client(model = vgg19)
848 174
849 175 # Run model for inference as usual
850 176 result = vgg19(input)
```

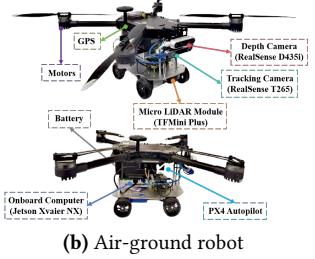
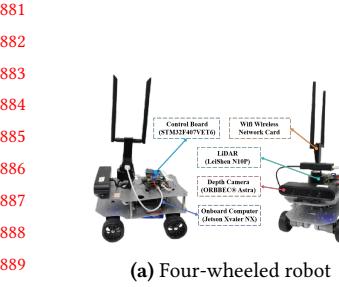
851 **Figure 5.** An example of applying Intra-DP to a VGG19 [45]  
 852 model, where “192.168.50.1” is the IP address of the GPU  
 853 server.  
 854  
 855

## 6 Evaluation

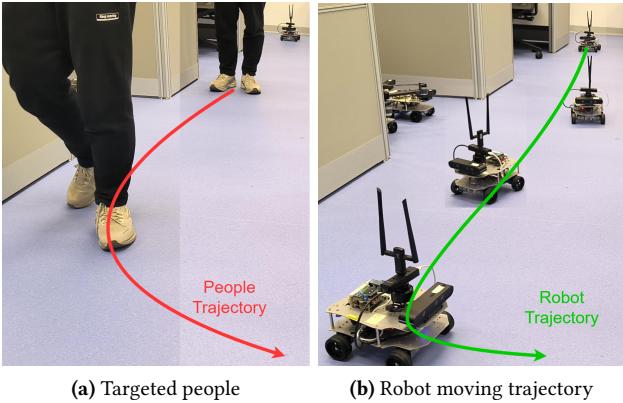
**Testbed.** The evaluation was conducted on a custom four-wheeled robot (Fig 6a), and a custom air-ground robot (Fig 6b). They are equipped with a Jetson Xavier NX [37] 8G onboard computer that is capable of AI model inference with local computation resources. The system runs Ubuntu 20.04 with ROS Noetic and a dual-band USB network card (MediaTek MT76x2U) for wireless connectivity. The Jetson Xavier NX interfaces with a Leishen N10P LiDAR, ORBBEC Astra depth camera, and an STM32F407VET6 controller via USB serial ports. Both LiDAR and depth cameras facilitate environmental perception, enabling autonomous navigation, obstacle avoidance, and SLAM mapping. The GPU server accepting offloaded computation tasks from the robot is a PC equipped with an Intel(R) i5 12400f CPU @ 4.40GHz and an NVIDIA GeForce GTX 2080 Ti 11GB GPU, connected to our robot via Wi-Fi 6 over 80MHz channel at 5GHz frequency in our experiments.

Tab. 3 presents the overall on-board energy consumption (excluding motor energy consumption for robot movement) of the robot in various states: inference (model inference with full GPU utilization, including CPU and GPU energy consumption), transmission (communication with the GPU

875  
 876  
 877  
 878  
 879  
 880



**Figure 6.** The detailed composition of the robot platforms



**Figure 7.** A real-time people-tracking robotic application on our robot based on a well-known human pose estimation ML model, Kapao [33].

912 server, including wireless network card energy consumption), and standby (robot has no tasks to execute). Notice 913 that different models, due to varying numbers of parameters, 914 exhibit distinct GPU utilization rates and power consumption 915 during inference. 916

917 **Experiment Environments.** We evaluated two real-world 918 environments: indoors (robots move in our laboratory with 919 desks and separators interfering with wireless signals) and 920 outdoors (robots move in our campus garden with trees and 921 bushes interfering with wireless signals, resulting in lower 922 bandwidth). The corresponding bandwidths between the 923 robot and the GPU server in indoors and outdoors scenarios 924 are shown in Fig. 2. 925

926 **Workload.** We evaluated two typical real-world robotic 927 applications on our testbed: Kapao, a real-time people-tracking 928 application on our four-wheeled robot (Fig 7), and AGRNav, 929 an autonomous navigation application on our air-ground 930 robot (Fig 8). These applications feature different model input 931 and output size patterns: Kapao takes RGB images as input 932 and outputs key points of small data volume. In contrast, 933 AGRNav takes point clouds as input and outputs predicted 934 point clouds and semantics of similar data volume as input, 935



**Figure 8.** By predicting occlusions in advance, AGRNav [50] gains an accurate perception of the environment and avoids collisions, resulting in efficient and energy-saving paths.

implying that AGRNav needs to transmit more data during offloading. And we have verified several models common to mobile devices on a larger scale to further corroborate our observations and findings: MobileNet [46], ResNet [48], VGGNet [45], ConvNeXt [52], RegNet [57].

**Baselines.** We selected two SOTA pipeline parallelism methods as baselines: DSCCS [26], aimed at accelerating inference, and SPSO-GA [5], focused on optimizing energy consumption. We set SPSO-GA’s deadline constraints to 1 Hz, the minimum frequency required for robot movement control. Given our primary focus on inference time and energy consumption per inference, we disabled pipeline execution to concentrate solely on assessing the performance of various layer partitioning methods.

## 6.1 Inference Time

**Kapao.** From the results in the upper part of Tab. 4, both SPSO-GA and DSCCS reduced Kapao’s inference time by 39.69% and 56.92% indoors and 28.67% and 47.46% outdoors, with DSCCS achieving 28.57% (indoors) and 26.34% (outdoors) lower inference time than SPSO-GA. While both systems significantly reduced inference time via offloading, transmission time accounts for 49.69% to 69.46% of the whole inference time, indicating that even with SOTA layer partitioning, the transmission bottleneck inherent to PP’s scheduling mechanism cannot be mitigated. The difference between DSCCS and SPSO-GA can be attributed to their optimization goals: DSCCS minimizes inference latency, while SPSO-GA minimizes power consumption under deadline constraints.

**AGRNav.** The performance gain of the two offloading systems varied for AGRNav, as shown in the lower part of Tab. 4. DSCCS still reduced inference time by 18.34% and 12.43% in indoors and outdoors. However, SPSO-GA achieved similar inference time (3.65% and 3.06% reduction) as local computation both indoors and outdoors. We will explain and analyze this phenomenon in Sec.6.2.

Notice that the large standard deviation in transmission time in outdoors in both offloading systems indicates that

Model(number of parameters)	Local computation time (s)	Environment	Transmission time (s)			Inference time (s)		
			DSCCS	SPSO-GA	Intra-DP	DSCCS	SPSO-GA	Intra-DP
kapao(77M)	0.78( $\pm 0.23$ )	indoors	0.228( $\pm 0.176$ )	0.235( $\pm 0.164$ )	0.259( $\pm 0.181$ )	0.343( $\pm 0.192$ )	0.311( $\pm 0.168$ )	0.264( $\pm 0.148$ )
		outdoors	0.087( $\pm 0.178$ )	0.35( $\pm 1.045$ )	0.385( $\pm 1.15$ )	0.696( $\pm 0.125$ )	0.434( $\pm 1.046$ )	0.369( $\pm 0.49$ )
agrnav(0M)	1.12( $\pm 0.11$ )	indoors	0.266( $\pm 0.166$ )	0.239( $\pm 0.149$ )	0.263( $\pm 0.164$ )	0.433( $\pm 0.134$ )	0.427( $\pm 0.12$ )	0.365( $\pm 0.50$ )
		outdoors	0.263( $\pm 0.843$ )	0.218( $\pm 0.796$ )	0.24( $\pm 0.875$ )	0.512( $\pm 0.779$ )	0.536( $\pm 0.72$ )	0.456( $\pm 0.52$ )

**Table 4.** Average transmission time (Second), inference time (Second), percentage that transmission time accounts for of inference time and their standard deviation ( $\pm n$ ) of Kapao and AGRNav with different pipeline parallelism offloading systems and different environments. “Local computation” refers to placing the whole layers on the robot.

Model(number of parameters)	Environment	Power consumption(W)			Energy consumption(J) per inference			
		Local	DSCCS	SPSO-GA	Intra-DP	Local	DSCCS	SPSO-GA
kapao(77M)	indoors	15.04( $\pm 0.64$ )	7.03( $\pm 3.57$ )	5.92( $\pm 2.18$ )	5.03( $\pm 1.87$ )	15.03( $\pm 0.63$ )	2.41( $\pm 1.35$ )	1.84( $\pm 1.0$ )
	outdoors	15.04( $\pm 0.64$ )	14.15( $\pm 1.71$ )	5.89( $\pm 2.3$ )	5.02( $\pm 1.97$ )	1.56( $\pm 0.85$ )	9.85( $\pm 1.77$ )	2.56( $\pm 6.17$ )
agrnav(0.84M)	indoors	10.26( $\pm 1.58$ )	6.6( $\pm 1.95$ )	6.74( $\pm 2.03$ )	5.74( $\pm 1.78$ )	10.82( $\pm 1.44$ )	2.86( $\pm 0.88$ )	2.88( $\pm 0.81$ )
	outdoors	10.26( $\pm 1.58$ )	7.36( $\pm 2.34$ )	7.91( $\pm 2.45$ )	6.71( $\pm 2.1$ )	10.82( $\pm 1.44$ )	3.77( $\pm 5.74$ )	4.25( $\pm 5.7$ )

**Table 5.** The power consumption against time (Watt) and energy consumption per inference (Joule) with standard deviation ( $\pm n$ ) of Kapao and AGRNav at different baselines and environments. “Local” represents “Local computation”

bandwidth fluctuated more frequently and more fiercely outdoors compared with indoors, which complies with Fig. 2. Additionally, the lower average bandwidth for outdoors scenarios (see Sec.2.1) results in increased transmission and inference times relative to indoor scenarios.

## 6.2 Breakdown

Both SPSO-GA and DSCCS automatically adapt to available bandwidth, transitioning to edge computation (placing all DNN layers on the GPU server) when bandwidth is sufficient, and to local computation (placing all DNN layers on robots) when bandwidth is low. To better understand how their layer partitioning scheduling varies with different network conditions and models, we recorded and analyzed the Categories and percentages of various layer partitioning schedules under different baselines and environments, as detailed in Fig. 9.

Local computation and edge computation are special cases of layer partitioning, with the bandwidth conditions required for each model to reach these cases varying based on the model structure and partitioning method used. Analyzing Fig. 9a and Fig. 9b, both SPSO-GA and DSCCS tend to allocate more layers on the robot for AGRNav. When comparing indoor and outdoor scenarios in Fig. 9, it is evident that higher bandwidth leads to more layers being scheduled on GPU server. Additionally, when comparing SPSO-GA and DSCCS in Fig. 9, DSCCS, which focuses on optimizing energy consumption, tends to place fewer layers on the robot to reduce computation energy consumption.

In summary, the conditions under which layer partitioning schemes make these special cases are influenced by multiple factors: model structure, and the trade-offs between inference delay and energy consumption. And the higher the bandwidth, the more layers are scheduled to be placed on GPU server.

## 6.3 Energy Consumption

**Kapao.** From the results in the upper part of Tab. 5, DSCCS consumed 3.38% and 2.02% more power per second than SPSO-GA indoors and outdoors due to more layers placed on robots shown in Fig. 9a. However, SPSO-GA consumed 58.54% and 49.74% more energy overall to process a frame than DSCCS because it only aims at minimizing the power consumption against time at the cost of possibly prolonged inference time.

**AGRNav.** From the results in the lower part of Tab. 5, DSCCS consumed 61.21% and 22.92% more energy per second than SPSO-GA indoors and outdoors ( Tab. 5), while DSCCS consumed 34.15% and 5.43% more energy to process a frame than SPSO-GA. SPSO-GA’s advantages in power consumption aganist time shrinks in energy consumption per inference due to prolonged inference time.

## 6.4 Validation on a larger range of models

We evaluated PP across a broad range of models with varying parameter counts (from 0.84M to 644M, as detailed in Tab. 6 and Tab. 7), which are commonly used in mobile devices. Our findings confirm that transmission time constitutes a significant portion of the total inference time in robotic IoT

Model(number of parameters)	Local computation time (s)	Environment	Transmission time (s)			Inference time (s)		
			DSCCS	SPSO-GA	Intra-DP	DSCCS	SPSO-GA	
MobileNet_V3_Small(2M)	0.025( $\pm 0.005$ )	indoors outdoors	0.048( $\pm 0.035$ ) 0.04( $\pm 0.161$ )	0.011( $\pm 0.032$ ) 0.008( $\pm 0.204$ )	0.012( $\pm 0.035$ ) 0.009( $\pm 0.224$ )	0.059( $\pm 0.036$ ) 0.054( $\pm 0.133$ )	0.042( $\pm 0.725$ ) 0.034( $\pm 0.573$ )	0.1158 0.1159 0.1160
RegNet_X_3_2GF(15M)	0.056( $\pm 0.004$ )	indoors outdoors	0.049( $\pm 0.035$ ) 0.046( $\pm 0.169$ )	0.026( $\pm 0.024$ ) 0.021( $\pm 0.12$ )	0.028( $\pm 0.027$ ) 0.024( $\pm 0.131$ )	0.063( $\pm 0.037$ ) 0.067( $\pm 0.136$ )	0.055( $\pm 0.212$ ) 0.063( $\pm 0.651$ )	0.1151 0.1161 0.1162
ResNet101(44M)	0.078( $\pm 0.002$ )	indoors outdoors	0.049( $\pm 0.035$ ) 0.048( $\pm 0.172$ )	0.033( $\pm 0.023$ ) 0.0( $\pm 0.0$ )	0.036( $\pm 0.025$ ) 0.0( $\pm 0.0$ )	0.064( $\pm 0.037$ ) 0.072( $\pm 0.135$ )	0.058( $\pm 0.017$ ) 0.0( $\pm 0.0$ )	0.1163 0.1164 0.1165
ConvNeXt_Base(88M)	0.139( $\pm 0.002$ )	indoors outdoors	0.049( $\pm 0.036$ ) 0.052( $\pm 0.178$ )	0.041( $\pm 0.041$ ) 0.032( $\pm 0.124$ )	0.045( $\pm 0.045$ ) 0.036( $\pm 0.137$ )	0.063( $\pm 0.037$ ) 0.079( $\pm 0.141$ )	0.061( $\pm 0.032$ ) 0.072( $\pm 0.093$ )	0.1165 0.1166 0.1167
VGG19_BN(143M)	0.097( $\pm 0.002$ )	indoors outdoors	0.049( $\pm 0.036$ ) 0.05( $\pm 0.172$ )	0.034( $\pm 0.024$ ) 0.031( $\pm 0.117$ )	0.038( $\pm 0.027$ ) 0.034( $\pm 0.129$ )	0.058( $\pm 0.036$ ) 0.07( $\pm 0.134$ )	0.054( $\pm 0.021$ ) 0.061( $\pm 0.085$ )	0.1167 0.1168 0.1169
ConvNeXt_Large(197M)	0.291( $\pm 0.002$ )	indoors outdoors	0.048( $\pm 0.035$ ) 0.056( $\pm 0.189$ )	0.049( $\pm 0.036$ ) 0.037( $\pm 0.136$ )	0.054( $\pm 0.039$ ) 0.04( $\pm 0.15$ )	0.068( $\pm 0.036$ ) 0.092( $\pm 0.149$ )	0.068( $\pm 0.036$ ) 0.09( $\pm 0.122$ )	0.1170 0.1171 0.1172

**Table 6.** Average transmission time (Second), inference time (Second), percentage that transmission time accounts for of inference time and their standard deviation ( $\pm n$ ) of common AI models in different environments with different offloading systems. “Local computation” refers to placing the whole layers on the robot.

Model(number of parameters)	Environment	Power consumption(W)				Energy consumption(J) per inference		
		Local	DSCCS	SPSO-GA	Intra-DP	Local	DSCCS	SPSO-GA
MobileNet_V3_Small(2M)	indoors outdoors	6.46( $\pm 0.12$ ) 6.46( $\pm 0.12$ )	5.21( $\pm 0.3$ ) 5.33( $\pm 0.61$ )	5.51( $\pm 0.65$ ) 5.79( $\pm 0.74$ )	4.94( $\pm 0.73$ ) 5.23( $\pm 0.83$ )	0.16( $\pm 0.04$ ) 0.16( $\pm 0.04$ )	0.31( $\pm 0.19$ ) 0.29( $\pm 0.71$ )	0.23( $\pm 4.0$ ) 0.2( $\pm 3.32$ )
RegNet_X_3_2GF(15M)	indoors outdoors	8.89( $\pm 0.2$ ) 8.89( $\pm 0.2$ )	5.11( $\pm 0.27$ ) 5.83( $\pm 1.57$ )	6.6( $\pm 1.2$ ) 7.03( $\pm 1.6$ )	5.96( $\pm 1.22$ ) 6.3( $\pm 1.55$ )	0.49( $\pm 0.04$ ) 0.49( $\pm 0.04$ )	0.32( $\pm 0.19$ ) 0.39( $\pm 0.79$ )	0.36( $\pm 1.4$ ) 0.45( $\pm 4.58$ )
ResNet101(44M)	indoors outdoors	9.78( $\pm 0.26$ ) 9.78( $\pm 0.26$ )	5.08( $\pm 0.26$ ) 6.05( $\pm 1.9$ )	6.31( $\pm 1.74$ ) 4.42( $\pm 0.34$ )	5.7( $\pm 1.66$ ) 3.99( $\pm 0.49$ )	0.76( $\pm 0.02$ ) 0.76( $\pm 0.02$ )	0.32( $\pm 0.19$ ) 0.44( $\pm 0.82$ )	0.36( $\pm 0.11$ ) 0.0( $\pm 0.0$ )
ConvNeXt_Base(88M)	indoors outdoors	10.64( $\pm 0.25$ ) 10.64( $\pm 0.25$ )	5.11( $\pm 0.25$ ) 6.19( $\pm 2.1$ )	6.09( $\pm 1.64$ ) 7.39( $\pm 2.53$ )	5.45( $\pm 1.53$ ) 6.63( $\pm 2.38$ )	1.48( $\pm 0.03$ ) 1.48( $\pm 0.03$ )	0.32( $\pm 0.19$ ) 0.49( $\pm 0.87$ )	0.37( $\pm 0.19$ ) 0.53( $\pm 0.69$ )
VGG19_BN(143M)	indoors outdoors	10.6( $\pm 0.37$ ) 10.6( $\pm 0.37$ )	5.15( $\pm 0.27$ ) 6.28( $\pm 2.2$ )	6.52( $\pm 2.06$ ) 7.45( $\pm 2.56$ )	5.84( $\pm 1.89$ ) 6.68( $\pm 2.38$ )	1.03( $\pm 0.02$ ) 1.03( $\pm 0.02$ )	0.3( $\pm 0.18$ ) 0.44( $\pm 0.84$ )	0.35( $\pm 0.14$ ) 0.46( $\pm 0.63$ )
ConvNeXt_Large(197M)	indoors outdoors	10.73( $\pm 0.44$ ) 10.73( $\pm 0.44$ )	5.11( $\pm 0.23$ ) 6.33( $\pm 2.34$ )	5.27( $\pm 0.2$ ) 7.5( $\pm 2.75$ )	4.75( $\pm 0.48$ ) 6.76( $\pm 2.56$ )	3.13( $\pm 0.02$ ) 3.13( $\pm 0.02$ )	0.35( $\pm 0.18$ ) 0.58( $\pm 0.94$ )	0.36( $\pm 0.19$ ) 0.67( $\pm 0.91$ )

**Table 7.** The power consumption against time (Watt) and energy consumption per inference (Joule) with standard deviation ( $\pm n$ ) of common AI models at different baselines and environments. “Local” represents “Local computation”

when using PP. The inherent transmission overhead of PP’s scheduling mechanism significantly wastes both inference time and energy.

## 6.5 Lessons learned

**Global optimal solution.** for nonlinear optimization problem

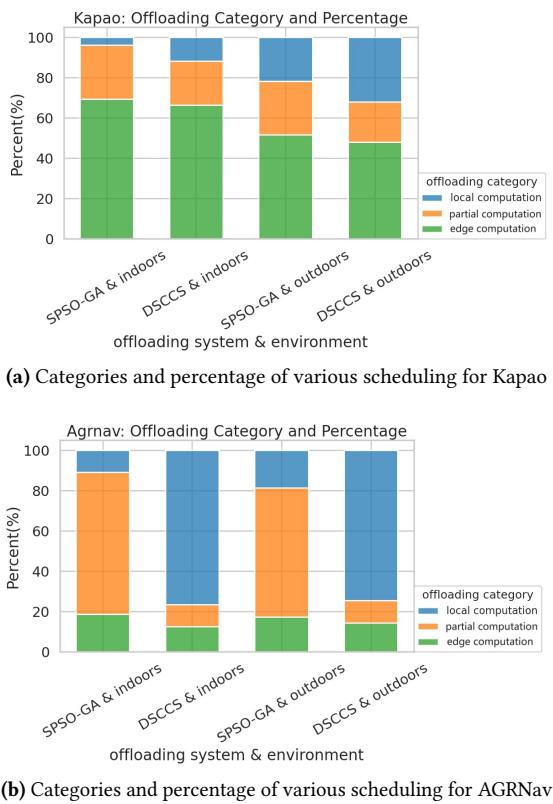
**Wireless bandwidth prediction.**

**Distributed inference system for multiple robots.**

## 7 Conclusion

In this paper, we present Intra-DP, a high-performance distributed inference system optimized for robotic IoT networks.

By breaking up the granularity of model inference into local operators via LOP and applying adaptive scheduling to the computation and transmission of each local operator via LOSS, Intra-DP dramatically reduces the transmission overhead in existing distributed inference on robotic IoT by overlapping the computation and transmission phases within the same inference task, achieving fast and energy-efficient distributed inference. We envision that the fast and energy-efficient inference of Intra-DP will foster the deployment of diverse robotic tasks on real-world robots in the field.



**Figure 9.** The layer partitioning scheduling under different baselines and environments. “Local computation” refers to placing the whole layers on the robot when the bandwidth is too low, “edge computation” means placing the whole layers on GPU server when the bandwidth is sufficient, and “partial computation” means placing part of the layers on the robot and part on GPU server.

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