

Intra-DP: A High Performance Collaborative Inference System for Mobile Edge Computing

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Abstract

Deep Neural Networks (DNNs) have revolutionized mobile applications in various domains. However, their deployment on resource-constrained mobile devices presents significant challenges in achieving real-time performance while managing limited computational resources and battery life. While Mobile Edge Computing (MEC) offers collaborative inference with GPU servers as a promising solution, existing approaches primarily rely on layer-wise model partitioning, which faces significant transmission bottlenecks caused by the sequential execution of DNN operations. To address this challenge, we present Intra-DP, a high-performance collaborative inference system optimized for DNN inference on MEC. Intra-DP employs a novel parallel computing technique based on local operators (i.e., operators whose minimum unit input is not the entire input tensor, such as the convolution kernel). By cutting their operations into several independent sub-operations and overlapping the computation and transmission of different sub-operations through parallel execution, Intra-DP significantly mitigates transmission bottlenecks in MEC, achieving fast and energy-efficient inference. The evaluation demonstrates that Intra-DP reduces inference time and per-inference energy consumption by up to 50% and 75%, respectively, compared to state-of-the-art baselines, without sacrificing accuracy.

1 Introduction

Deep Neural Networks (DNNs) have powered a wide range of mobile applications, from intelligent wearable sensors [13, 59] and autonomous vehicles [5, 69] to smart manufacturing systems [85, 97]. These applications are built upon fundamental advances in object detection [35, 49, 54], robotic control [41, 78, 89], and environmental perception [11, 42, 82], all of which demand fast inference for swift responses. Deploying DNN models on real-world mobile devices (e.g., smartphones and IoT devices) presents two major challenges: the need for fast inference and the limitation of computing resources, including computational power and battery life.

Recent studies [2, 8, 29, 33, 56, 87, 95] have proposed mobile edge computing (MEC) as a promising solution for fast and energy-efficient inference by leveraging GPU servers at the edge of the radio access network. Conventional MEC approaches (illustrated in Fig. 1) are categorized into device-only, server-only, and collaborative inference [14, 43, 72]. Device-only inference is constrained by limited on-device computing resources (Sec. 2.1), while server-only inference

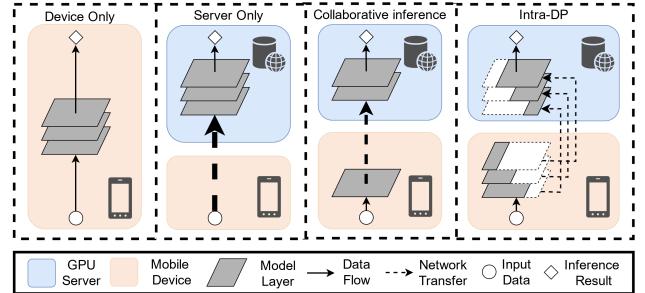


Figure 1: Comparison between conventional Mobile Edge Computing approaches and Intra-DP. Inference results computed on the GPU server must be transmitted back to the mobile device for application utilization.

suffers from bandwidth limitations (Sec. 2.2). Collaborative inference achieves a better balance between computation and communication through layer-wise model partitioning (layer partitioning), which distributes DNN layers across mobile devices and GPU servers. Since some intermediate layers produce significantly smaller activations than raw input data [29], this approach reduces transmission overhead and further optimizing resource utilization (Sec. 2.3).

However, despite its advantages, the sequential nature of layer partitioning introduces significant transmission delays, making it a major bottleneck for collaborative inference in MEC environments. Existing methods enforce strictly sequential execution, consisting of early-layer computation on mobile devices, intermediate result transmission, and final inference on GPU servers. Limited network bandwidth capacity (due to MEC network limitations and practical instability, Sec. 2.2) prolongs transmission (about half of inference time in our experiments), causing significant idle periods on mobile devices. This not only increases overall inference time but also results in significant energy waste (around 40%). Although pipeline execution [15, 22, 23] attempts to alleviate transmission bottlenecks by overlapping computation and communication across multiple requests, its primary benefit lies in improving throughput rather than reducing the inference time of individual requests, which is a crucial requirement for real-time mobile applications.

To address these limitations, a parallel execution strategy that overlaps computation and communication within a single inference request offers a promising alternative. Unlike traditional sequential execution, this approach allows computation and data transmission to proceed concurrently, significantly reducing idle time on mobile devices. This not

only speeds up inference but also improves energy efficiency, as idle-period energy consumption is primarily driven by core components such as the CPU, GPU, and memory modules [37] (95% of total energy in our experiment), while wireless network interface cards contribute only 1.5%.

However, implementing this parallel computing technique poses three key challenges. ① Traditional parallel computing methods (data, tensor, and pipeline parallelism) work well in data centers but struggle in MEC due to batch size limits, high synchronization costs, and transmission delays (Sec. 2.4), necessitating a finer-grained scheduling unit. ② Fine-grained parallelism is vulnerable to consistency issues, where the failure or error of any single unit (e.g., receiving incorrect input) can compromise the entire inference result. ③ Minimizing latency and energy consumption requires a new scheduling paradigm to balance computation and transmission, but finer-grained scheduling increases the search space from $O(n)$ (layer-wise) to $O(n^2)$, complicating optimization.

To address these challenges, we propose Intra-DP (Intra-Data Parallel), a high-performance collaborative inference system optimized for MEC environments. ① Intra-DP introduces a novel parallel computing technique that defines scheduling units based on local operators, where the minimum input is a subset of the full tensor (e.g., individual elements for ReLU [16], tensor blocks for convolution [56]). Their operations can be decomposed into independent sub-operations, enabling those in subsequent layers to start execution as soon as their required inputs are ready, without waiting for all sub-operations in the current layer to complete. This enables finer-grained parallel scheduling, achieving computation-communication overlap within a single inference request. ② To ensure result correctness and completeness, Local Operation Parallelism (LOP) manages data dependencies between operations, where one operation's output serves as another's input, ensuring each operator receives the correct input and propagates the correct output during parallel execution. ③ To achieve fast and energy-efficient inference, Local Operation Scheduling Strategy (LOSS) formulates scheduling as a constrained optimization problem, and optimally distributes local operations between mobile devices and GPU servers, using a solution derived from differential evolution [68].

In summary, this paper makes the following contributions:

- We propose Intra-DP, a novel collaborative inference system that enables fine-grained parallel scheduling based on local operators, specifically optimized for MEC environments. The code is released on <https://github.com/mobicom25paper676/intraDP>.
- We develop a comprehensive parallel computing technique that guarantees inference correctness based on local operations while enabling efficient computation-transmission overlapping.

- We design an innovative scheduling algorithm leveraging LOP to optimize both inference speed and energy efficiency.
- We implement an adaptive control mechanism integrated with LOSS to dynamically handle real-time network bandwidth fluctuations in MEC environments.
- We empirically evaluate Intra-DP through extensive experiments, demonstrating its superiority over state-of-the-art baselines in MEC environments in terms of inference latency and energy efficiency. Specifically, Intra-DP reduces inference time by up to 50% and per-inference energy consumption by up to 75% compared to baselines without sacrificing accuracy.

2 Background and Motivation

2.1 Device-only Inference

Device-only inference, which deploys DNN models directly on mobile devices, is severely constrained by the limited computational power of processors and battery capacity. As shown in Fig. 2a, the inference latency on these devices exceeds the 30ms threshold required for smooth video fluency [25, 26] (indicated by the red dotted line). Moreover, Fig. 2b demonstrates that frequent model inference significantly reduces device standby time to just 20–40% of its normal duration, severely affecting user experience and overall device practicality.

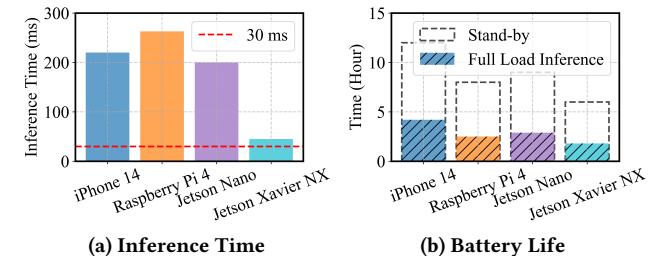


Figure 2: The performance of VGG-16 under device-only inference across different mobile devices [7, 10, 55, 58, 62, 64].

2.2 Server-only Inference

Server-only inference, which deploys DNN models directly on a GPU server, is susceptible to long tail delays and requires substantial bandwidth for data transmission. As shown in Fig. 3, under the same testbed settings as Sec. 5 (a robot equipped with a Jetson Xavier NX [62] and a GPU server with an NVIDIA GeForce GTX 3080), inference time increases sharply as bandwidth decreases. However, in real-world scenarios, mobile devices primarily rely on wireless networks, which offer high mobility but limited bandwidth capacity compared to data center networks equipped with high-speed technologies such as InfiniBand [61] or PCIe [40] (40–500 Gbps).

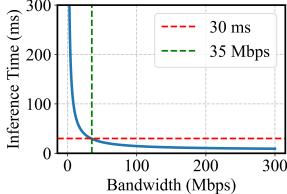


Figure 3: The inference time of VGG-16 under server-only inference across different network bandwidth.

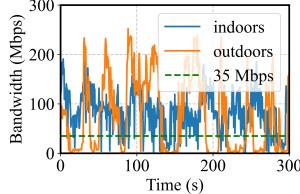


Figure 4: The wireless transmission instability of TCP between our robot and the base station in MEC networks.

The bandwidth capacity of wireless networks is inherently constrained by both theoretical limits and practical challenges in MEC. While Wi-Fi 6 can achieve a peak bandwidth of 1.2 Gbps per stream [48], mobile devices lack the necessary hardware to fully leverage this capacity [88]. Furthermore, the actual available bandwidth varies significantly due to factors such as device mobility [53, 63], signal obstruction [18, 71], and channel contention [3, 70], further limiting effective bandwidth.

To examine wireless instability in MEC scenarios, we conducted a robot surveillance experiment where four-wheeled robots navigated through a lab (indoors) and a campus garden (outdoors) at speeds of 5–40 cm/s. Using iperf [1], we measured real-time wireless bandwidth capacity between the robot and a base station over TCP [76] at 0.1-second intervals for five minutes. As shown in Fig. 4, the average bandwidth was 93 Mbps indoors and 73 Mbps outdoors, with outdoor measurements exhibiting higher fluctuations and occasional near-zero drops due to obstacles and reduced signal reflections, indicating that server-only inference is difficult to sustain under realistic wireless network conditions.

2.3 Existing Collaborative Inference

Existing collaborative inference methods [8, 14, 29, 33, 43, 56, 87, 95] primarily focus on layer partitioning to balance inference time and energy consumption, as shown in Fig. 5. “Layer 0” represents server-only inference, where all model layers run on a GPU server, and transmission time varies with network bandwidth, even under the same partitioning strategy. These methods can be categorized by their optimization objectives: accelerating DNN inference [29, 36, 43, 56, 87] or minimizing energy consumption under deadline constraints [14, 44, 81]. The widespread adoption of layer partitioning in mobile applications has drawn significant research attention [8, 29, 33, 56, 87, 95], as optimal strategies depend on multiple factors, including model architecture, hardware capabilities (e.g., GPU servers and mobile devices), network conditions, and application-specific trade-offs between inference speed and energy efficiency. However, all existing methods [8, 14, 29, 33, 36, 43, 44, 56, 81, 87, 95] are inherently constrained by transmission delays due to the

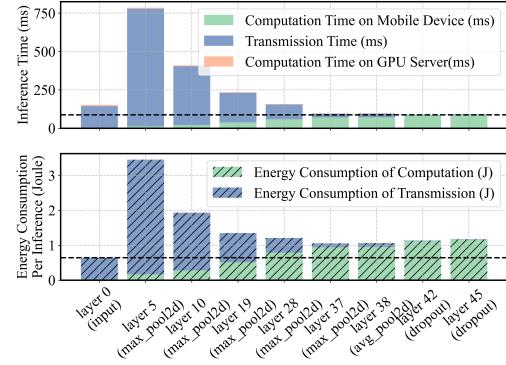


Figure 5: The performance of different layer partitioning strategies for VGG-19 under 35 Mbps in our experiments. The X-axis represents various partitioning points, where ‘layer i ’ denotes that all layers up to and including the i^{th} layer are executed on the robot, while the remaining layers are offloaded to the GPU server.

sequential nature of layer partitioning, a limitation that can be effectively addressed by Intra-DP.

2.4 Related Parallel Computing Techniques

Parallel computing techniques have been extensively explored and proven effective in modern data centers [31, 83, 98]. However, they are unsuitable for MEC due to fundamental differences in computational constraints and latency requirements. The three primary parallelism strategies in data centers are data parallelism (DP), which replicates the model across devices and processes mini-batches in parallel; tensor parallelism (TP), which partitions computations within a layer across multiple devices; and pipeline parallelism (PP), which distributes different layers of DNN model across devices (layer partitioning) and executes them in a pipelined manner (pipeline execution) to reduce idle time.

DP’s efficiency is fundamentally constrained by batch size requirements [57]. In data centers, large batch sizes (e.g., 16 images) are split into mini-batches (e.g., 2 images each), maintaining computational efficiency. However, MEC requires real-time inference with minimal latency, typically processing a single input at a time (e.g., 1 image). Further splitting such small inputs into sub-mini-batches (e.g., 1/4 of an image) is impractical, making DP inefficient. Some methods [93, 96] split input images across an IoT device group based on computational power, but in MEC environments with GPU servers, this approach loses effectiveness. The significant computational disparity between mobile devices and GPU servers leads to a near-complete reliance on server-side execution, essentially degrading into server-only inference.

TP enables parallel computation within a single layer across devices but incurs substantial communication overhead due to the required all-reduce synchronization [98]. We evaluated DINA [56], a state-of-the-art TP method, on our testbed (Sec.5). As shown in Fig.6, the excessive all-reduce

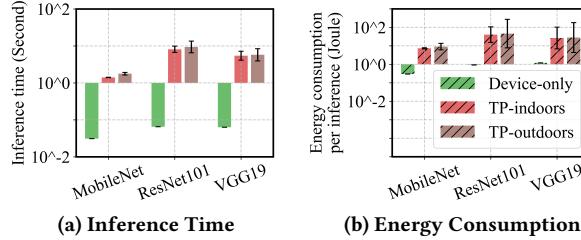


Figure 6: The performance of TP for different models.

overhead results in $45.2\times$ to $143.9\times$ longer inference time and $28.5\times$ to $62.7\times$ higher energy consumption per inference than device-only inference. While there have been efforts to reduce the communication overhead of TP in data centers, such as distributing each layer along both the spatial and temporal dimensions [77], these methods remain ineffective in MEC due to the persistent all-reduce requirement. In contrast, Intra-DP eliminates this communication for local operators, further reducing overhead.

PP employs pipeline execution to enhance throughput by overlapping computation and communication across multiple requests. However, this approach does not reduce the completion time of a single inference [15, 22, 23]. SPINN [39] attempts to optimize transmission efficiency through an early-exit policy combined with layer partitioning. While this reduces the number of transmissions by trading off accuracy, it introduces unpredictable and incorrect inference results, and requires careful expert tuning of parameters. Additionally, transmission delays persist in SPINN, an issue that can be effectively addressed by Intra-DP.

In conclusion, conventional parallel computing techniques, despite their success in data centers, are unsuitable for MEC. DP is constrained by batch size limitations, TP suffers from excessive synchronization overhead, and PP’s pipeline execution focuses on throughput rather than reducing inference latency. Consequently, existing collaborative inference in MEC relies on layer partitioning, which enforces sequential execution and introduces transmission delays, making them a major bottleneck for low-latency inference.

3 System Overview

In this section, we introduce Intra-DP, a high-performance collaborative inference system optimized for MEC environments. In this setting, resource-constrained mobile devices (e.g., robots, drones, smartphones) collaborate with GPU servers through wireless networks (e.g., Wi-Fi 6/5G) to achieve real-time and energy-efficient inference on local inputs.

3.1 Key Insight

Existing methods are limited to layer partitioning, which enforces serial execution and limits parallelism. Each DNN layer comprises one or more operators (e.g., convolution [56], softmax [50]), which must be executed sequentially to ensure computational correctness. As a result, current approaches

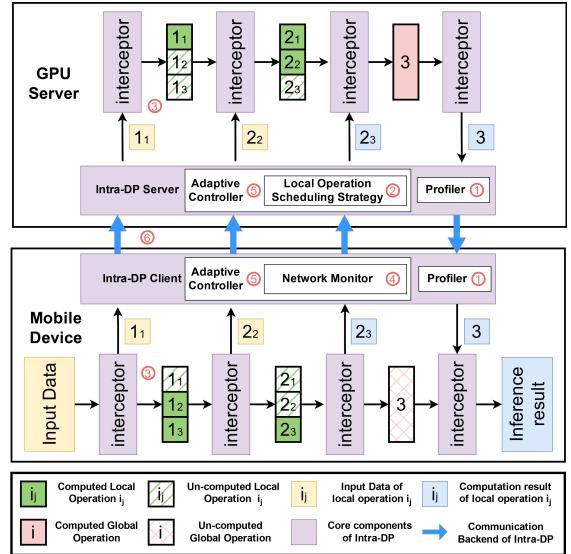


Figure 7: Overview and inference workflow of Intra-DP. Local operation i_j represents the j -th local operation within the i -th operator of the model.

can only partition these serial execution sequences at the layer level, restricting opportunities for parallel execution.

Our key insight is that, although operators are the smallest computation units at the system level, their computations (operation) can still be decomposed into several independent sub-operations based on their computational properties. Specifically, local operators, whose computations do not require access to the entire input tensor, enable finer-grained parallel execution. While existing methods treat each operator’s computation as an indivisible operation (e.g., a full convolution for a kernel), Intra-DP leverages this by treating each individual computation within a local operator, based on its minimal input unit, as an independent local operation. Since these local operations are independent, those in subsequent layers can be computed as soon as their required inputs are ready, without waiting for all operations in the current layer to finish. This independence enables a new parallelization opportunity within serial execution sequences, breaking the strict sequential execution constraint.

3.2 Overall Workflow

As illustrated in Fig. 7, Intra-DP consists of three integrated stages: Profiling, Scheduling Optimization, and Runtime.

The first stage, Profiling (①), is an offline process that collects essential runtime traces for Scheduling Optimization. It runs only once and captures key execution characteristics, including: i) operator types and input/output sizes; ii) execution times of operations on the mobile device and GPU server; iii) data dependencies between operations (i.e., the output of one operation serves as the input for another).

Using this profiling data, the system enters the Scheduling Optimization stage, where it applies Local Operation Scheduling Strategy (Sec. 4.3, ②) to achieve low-latency, energy-efficient inference. This strategy determines the optimal distribution of local operations, balancing computational workload and transmission synchronization. To mitigate the impact of network fluctuations, Intra-DP precomputes optimal scheduling plans for varying network bandwidth conditions in 1 MB intervals within the typical MEC bandwidth range (0~50 MB), eliminating runtime optimization overhead.

During Runtime, Intra-DP utilizes Operator Interceptors (Sec. 4.1, ③) to manage input/output tensor partitioning and reconstruction for each operator, enabling partial tensor processing based on local operations. To ensure reliability in MEC environments, the system continuously monitors network conditions utilizing established tools [90] (④) and Adaptive Controllers (Sec. 4.4, ⑤) dynamically adjust scheduling strategies based on real-time bandwidth fluctuations, ensuring stable performance. Then, Local Operation Parallelism (Sec. 4.2, ⑥) enables parallel execution between the client and server while preserving data dependencies for correct inference. To support seamless transitions between different schedules without delays, Intra-DP maintains a model replica on the GPU server (Fig. 7), allowing instant adaptation to network variations.

Despite these optimizations, Intra-DP introduces negligible overhead beyond the original inference process. The only additional cost stems from tensor splitting and combining. However, the impact of tensor splitting is effectively hidden due to concurrent data transmission and computation. While tensor combining introduces potential waiting time due to data dependencies, LOSS minimizes this impact by formulating the waiting overhead as a nonlinear optimization problem and solves it efficiently. This careful design ensures that the system of Intra-DP maintains high execution efficiency with minimal extra cost.

4 Detailed Design

4.1 Local Operators and Global Operators

Since the performance gains of Intra-DP rely on the parallel execution of local operations, it is crucial to determine the minimal input unit required for each operator based on its computational characteristics. To achieve this, Intra-DP employs Operator Interceptors (Fig. 7 ③) to handle input/output tensor partitioning and reconstruction, enabling partial tensor processing, and classify operators into local and global categories: local operators process only a subset of the input tensor, whereas global operators require the entire tensor. We identify three common types of local operators in models commonly used on mobile devices (mobile models):

- Element-wise local operators operate on individual tensor elements and are widely used in activation functions such as ReLU [16], Sigmoid [91], and SiLU [34]. However, activation functions like softmax [50] require access to the entire input tensor and are therefore global operators.
- Block-wise local operators process tensor blocks at corresponding positions, commonly found in convolution-related layers such as convolution [56] and max pooling [74]. The block size is determined by the operator's parameters (e.g., kernel size, padding, dilation) [66].
- Row-wise local operators operate on individual rows of the input tensor and are widely used in matrix operations such as addition [92] and multiplication [21]. These operations split the input matrix by rows, ensuring that each device processes an independent subset while sharing the same layer parameter matrix. According to matrix calculation principles as following, the computation of row a_1 results in $(c_{11} \dots c_{1n})$, which is itself a row and can be directly processed by subsequent matrix operators in the same manner, eliminating the need for all-reduce communication.

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

Unlike TP, which partitions the layer parameter matrix and replicates the full input matrix across multiple devices, row-wise local operators allow independent row processing across devices while maintaining a shared parameter matrix, avoiding all-reduce communication. Moreover, LOP treats operators with layer parameter matrices containing only one row as global operators.

Models with many local operators, prevalent in mobile models such as CNNs for computer vision [54] and point cloud processing [78], can benefit from Intra-DP through parallel execution. Table 1 quantifies their distribution across several mobile models based on the above definition.

| Model | Local / Global | Model | Local / Global |
|---------------|----------------|---------------|----------------|
| DenseNet [32] | 428 / 3 | RegNet [86] | 231 / 3 |
| ResNet [75] | 341 / 3 | VGGNet [73] | 73 / 5 |
| ResNeXt [84] | 342 / 3 | ConvNeXt [80] | 340 / 6 |

Table 1: Number of local/global operators in mobile models.

While local operators dominate CNN-based models, transformer-based models rely on self-attention mechanisms, which use softmax [50], a typical global operator, to compute attention weights over entire input sequences [30]. Since each transformer layer contains at least one global operator, the performance gains of Intra-DP over existing collaborative inference methods are limited, as its advantages primarily come

from parallelizing local operations, which is constrained by the presence of global operators. However, Intra-DP still outperforms existing methods by enabling parallel execution of local operations between consecutive global operators and seamlessly falling back to conventional layer partitioning when handling models without local operators. Although transformer-based models are rarely deployed directly on mobile devices, their increasing adoption motivates us to further enhance Intra-DP. As future work, we will support more types of local operators and develop lightweight synchronization techniques for global operators, such as synchronizing only the sum results in softmax [50] instead of transferring the entire input tensor, to reduce synchronization overhead and enhance Intra-DP's applicability.

4.2 Local Operation Parallelism

In this section, we demonstrate how Intra-DP ensures inference correctness based on local operators and how LOP achieves low latency and energy efficiency through the parallel execution of local operations (Fig. 7 ⑥).

LOP guarantees inference correctness by comprehensively managing dependencies between local and global operators. It tracks data dependencies to ensure that the output of one operation is correctly used as the input for subsequent operations, considering a dependency established if any part of the output serves as input. For local operators, it preserves computational correctness by enforcing the appropriate execution sequence and ensuring that each operation receives the correct input (either a raw input data or the output from a preceding operation) based on the DNN model structure and operator computation logic. For global operators, synchronization barriers are introduced to guarantee that all required input tensors are fully assembled before execution. By maintaining proper data flow throughout the inference process, this approach guarantees correctness across both local and global operators.

Fig. 8 compares the workflow of LOP with conventional TP and PP (layer partitioning). To reduce transmission overhead, LOP employs two key optimizations. First, it overlaps computation and transmission for different local operations to maximize execution efficiency (e.g., transmitting the input for 'LO₁₁' while computing 'LO₁₂', 'LO₁₃', and 'LO₂₁' on the robot). Second, it exploits data locality by prioritizing execution on devices that already contain the required input (e.g., 'LO₂₁' directly using the output of 'LO₁₁' on the GPU server). Unlike TP, which suffers from high communication costs due to frequent all-reduce synchronization, LOP limits synchronization to global operators only, eliminating unnecessary data transfers. Although LOP incurs finer-grained communication and a higher volume than PP, its early overlapping strategy effectively reduces overall transmission time, outperforming PP's sequential execution for individual inference

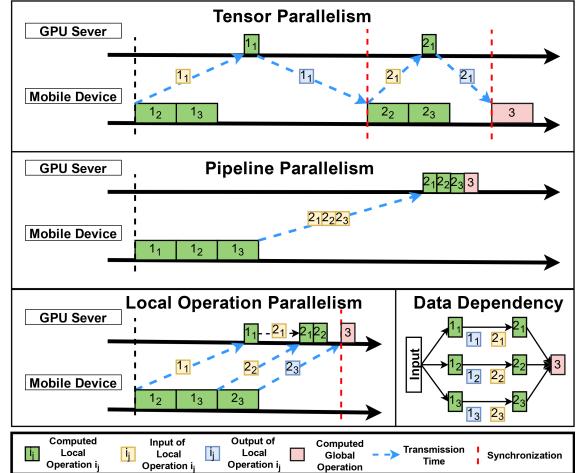


Figure 8: Workflow of TP, PP and LOP. In the three cases above, each local operator executes three operations with identical computation times on both the mobile device and the GPU server, along with the corresponding transmission time, while the lower right corner illustrates the data dependencies between operations.

requests. By efficiently overlapping computation and communication, Intra-DP minimizes idle time on mobile devices, accelerating inference and enhancing energy efficiency, as idle-period energy consumption is primarily dominated by core components such as the CPU, GPU, and memory modules rather than the wireless network interface cards.

4.3 Local Operation Scheduling Strategy

In this section, we detail how Intra-DP optimizes computation and transmission scheduling for local operations, achieving fast and energy-efficient inference (Fig. 7 ②).

LOSS formulates local operation scheduling as a constrained optimization problem, efficiently solved via differential evolution [68]. To streamline heterogeneous operation integration, it unifies global and local operations by treating global operators as special cases that aggregate all outputs from preceding local operations. The key performance boost stems from computation-communication overlapping, where LOSS leverages data locality by prioritizing execution on devices that already contain the required input. To further optimize scenarios where multiple operations on mobile devices and GPU servers simultaneously depend on the same output, especially in block-wise operations, LOSS introduces local operation replication, selectively duplicating operations across devices. This strategy incurs minimal computational redundancy but significantly reduces data transmission costs, particularly benefiting distributed operations that share input dependencies.

4.3.1 DNN Execution Model A deep neural network (DNN) is represented as a directed acyclic graph $G = (V, E)$, where vertices V denote layers (operators) and edges E indicate data dependencies. Two virtual vertices, *input* and *output*,

represent the model’s initial input and final inference result. The execution spans two instances: one on a resource-constrained mobile device (M) and the other on a GPU server (R).

4.3.2 Variables and Functions We treat each calculation of an operator based on its minimum input unit as an operation, and define $OP(v)$ as the set of operations for vertex v , where global operators always have $|OP(v)| = 1$. Operation allocations to M and R are represented by $x_M(v), x_R(v) \subseteq OP(v)$, with overlaps ($x_M(v) \cap x_R(v) \neq \emptyset$) occurring when local operations are replicated, especially for block-wise operators.

Execution starts at times $s_M(v), s_R(v) \geq 0$, and computation durations on each device are estimated as $C_M(v)$ and $C_R(v)$. If no operation is performed on a device, its computation time is zero. Data transmission times include $T_{MR}(u, v)$ for sending data from M to R and $T_{RM}(u, v)$ for the reverse direction, both determined by network bandwidth and dependent on the volume of input/output data associated with the respective operations.

4.3.3 Objective Function The goal is to minimize end-to-end inference latency while ensuring that the final results are available on the mobile device, thereby reducing its idle time:

$$\min T = s_M(output), \quad (2)$$

4.3.4 Constraints Data Partitioning Constraints. To ensure correctness, all operations must be executed: $x_M(v) \cup x_R(v) = OP(v), \forall v \in V$.

Location Constraints. Input data is initially available on M , ensuring $x_M(input) = input$ and $x_R(input) = \emptyset$. Similarly, the final results must reside on M , so $x_M(output) = output$ and $x_R(output) = \emptyset$.

Data Dependency Constraints. Operations start only after receiving all required inputs. For each v with parent connections $e = (u, v)$, execution on M follows:

$$s_M(v) = \begin{cases} s_M(u) + C_M(u), & \text{if } x_M(v) - child(x_M(u)) = \emptyset, \\ \max(s_R(u) + C_R(u) + T_{RM}(u, v), & \\ s_M(u) + C_M(u)), & \text{if } x_M(v) - child(x_M(u)) \neq \emptyset. \end{cases} \quad (3)$$

Here, $child(x(u))$ denotes the set of operations consuming outputs of $x(u)$ according to their data dependencies, and the transmission volume in $T_{MR}(u, v)$ is given by $x_M(v) - child(x_M(u))$. When $x_M(v) - child(x_M(u)) = \emptyset$, all required inputs for $x_M(v)$ are produced by operations on M ; otherwise, $x_M(v)$ also depends on outputs from operations executed on R . Similar constraints apply to R .

Computational Efficiency Constraints. To reduce excessive kernel launch overhead from input fragmentation while LOSS processes minimal input units, Intra-DP adopts operation batching, which consolidates multiple operations

into a single system-level kernel launch, to avoid redundant launches. By managing the partitioning and reconstruction of input/output tensors for each operator, this approach preserves fine-grained control over local operations while minimizing redundant executions. To formalize this, for all operators $v \in V$: $x_M(v) = \{i \mid i \in [\min(x_M(v)), \max(x_M(v))]\}$, $x_R(v) = \{i \mid i \in [\min(x_R(v)), \max(x_R(v))]\}$.

Transmission Efficiency Constraints. Building on the insight from existing layer partitioning methods that certain intermediate DNN layers produce significantly smaller outputs than raw input data [29], we impose the following constraints to minimize transmission overhead by eliminating redundant data transfers whenever possible. This also substantially reduces the search space, significantly accelerating the solving process of LOSS. For layers u whose outputs exceed the raw input size ($u \in \Pi$), with all $e = (u, v) \in E$: $x_M(v) - child(x_M(u)) = \emptyset$, and $x_R(v) - child(x_R(u)) = \emptyset$.

4.3.5 Solution Algorithm As the search space increases from $O(n)$ (layers) to $O(n^2)$ (operations), LOSS employs differential evolution [68], leveraging its strong global search capability and parallelism to efficiently solve the non-linear, non-convex scheduling problem. Given fixed hardware, bandwidth emerges as the dominant variable affecting local operation partitioning. This allows the problem to be addressed within a constrained search space, eliminating the exploration overhead of reinforcement learning [38].

While solving takes tens of minutes per model, it is performed offline within the Scheduling Optimization stage and does not impact runtime inference. Scheduling plans only need to be updated when hardware configurations change, such as upgrades to the mobile device’s computing accelerator or GPU server. Although Intra-DP’s system performance is directly influenced by solution quality, and achieving global optimality in non-convex problems remains challenging, future research will focus on refining algorithms to enhance solution quality, ultimately improving scheduling efficiency and overall system performance.

4.4 Adaptive Control Mechanism

To ensure efficient inference under varying network conditions, we assume stable bandwidth during each request, as model inference time (tens to hundreds of milliseconds) is finer-grained than wireless bandwidth fluctuations (a few seconds [65]). The adaptive control mechanism of Intra-DP runs on both the mobile device client and GPU server (Fig. 7 ⑤), with detailed algorithms in Alg.1 and Alg.2. During runtime, Intra-DP estimates real-time bandwidth (line 1 in both algorithms) and selects a suitable scheduling plan. It then computes the designated local operations (line 5 in both algorithms), producing outputs that represent the computation results of these local operations or an empty set if no local computation is performed. Leveraging operation

Algorithm 1: Intra-DP client at runtime stage

Input: Data input for inference $input$; DNN model $model$
Output: The inference result ret

Data: $Input(i), Output(i)$: input and output of layer i ; x_M^b ,
 x_R^b : schedule plan under the b bandwidth.

```

1  $b = TestBandwidth()$ 
2  $Input(0) = input$ 
3 foreach layer  $u$  in  $model$  do
4   if  $Input(u) \neq \emptyset$  and  $x_M^b(u) \neq \emptyset$  then
5     |  $output(u) = compute(Input(u), x_M^b(u))$ 
6   end
7   foreach edge  $e = (u, v) \in E$  do
8     | if  $x_M^b(v) - child(x_M^b(u)) \neq \emptyset$  then
9       |   |  $Input(v) =$ 
10      |   |  $combine(Output(u), ReceiveFromServer())$ 
11    | end
12    | if  $x_R^b(v) - child(x_R^b(u)) \neq \emptyset$  then
13      |   |  $SendToServer(Output(u), x_R^b(v) - child(x_R^b(u)))$ 
14    | end
15  end
16   $ret = Output(t)$ 
17 return  $ret$ 

```

Algorithm 2: Intra-DP server at runtime stage

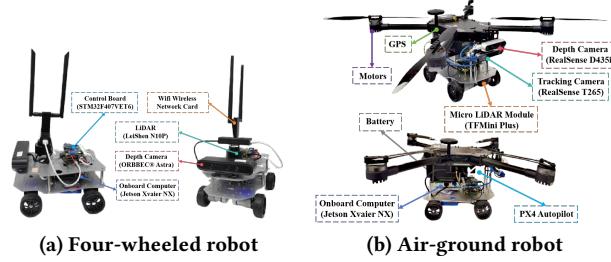
```

1  $b = ReceiveFromClient()$ 
2  $Input(0) = \emptyset$ 
3 foreach layer  $u$  in  $model$  do
4   if  $Input(u) \neq \emptyset$  and  $x_R^b(u) \neq \emptyset$  then
5     |  $output(u) = compute(Input(u), x_R^b(u))$ 
6   end
7   foreach edge  $e = (u, v) \in E$  do
8     | if  $x_M^b(v) - child(x_M^b(u)) \neq \emptyset$  then
9       |   |  $SendToClient(Output(u), x_R^b(v) - child(x_R^b(u)))$ 
10    | end
11    | if  $x_R^b(v) - child(x_R^b(u)) \neq \emptyset$  then
12      |   |  $Input(v) =$ 
13      |   |  $combine(Output(u), ReceiveFromClient())$ 
14    | end
15  end

```

batching from LOSS's computational efficiency constraints, Intra-DP merges all operations within the same operator ($x_M^b(u)$) into a single kernel launch. This launch executes once the required inputs are ready, prioritizing inference correctness over strict adherence to the scheduled execution time ($s_M(u)$). The associated blocking overhead, primarily from tensor combining, is optimized in LOSS.

If the scheduling plan requires data transmission, the server sends the computed outputs to the client (line 9 in Alg.2), which integrates them with its results for subsequent operators (line 9 in Alg.1). Similarly, if data needs to be sent

**Figure 9: The detailed composition of the robot platforms.**

| | inference | communication | standby |
|---------------|-----------|---------------|---------|
| Energy (Watt) | 13.35 | 4.25 | 4.04 |

Table 2: Power draw (Watt) of our robot in different states.

from client to server, the client transmits the outputs (line 12 in Alg.1), and the server integrates them accordingly (line 12 in Alg.2). Otherwise, the outputs of the current operator directly serve as inputs for subsequent operators. Once all operations are completed, the final inference result remains on the client, ready for upper-layer applications (line 17 in Alg.1).

5 Implementation

In this section, we first elaborate on the implementation of Intra-DP, and we then introduce the experiment setup.

5.1 System Implementation

5.1.1 Software We implement Intra-DP using Python and PyTorch [67], integrating it seamlessly into existing deep learning workflows. The implementation hooks into the model's forward method, where the first forward pass profiles the model using PyTorch's default profiler and execution schedule. Based on this profiling data, Intra-DP then intercepts and parallelizes all subsequent forward calls according to the optimized execution plan. With a lightweight integration requiring only three lines of code, Intra-DP ensures ease of deployment in existing applications.

5.1.2 Hardware Testbed We evaluate Intra-DP on two customized robotic platforms: a four-wheeled ground robot (Fig. 9a) and an air-ground hybrid robot (Fig. 9b). Each robot is equipped with a Jetson Xavier NX (8GB) [62], enabling on-board model inference with local computation. The system runs Ubuntu 20.04 with ROS Noetic and uses a dual-band USB network adapter (MediaTek MT76x2U) for wireless communication. Detailed hardware and sensor configurations are shown in Fig. 9. The GPU server is a PC equipped with an Intel i7-7700K CPU and an NVIDIA GeForce RTX 3080 GPU. It connects to the robots via Wi-Fi 6 on an 80MHz channel at 5GHz. Tab. 2 summarizes the robots' on-board energy consumption (excluding motor power) in different states: inference (full GPU utilization, including CPU/GPU power), communication (communication with the GPU server, including wireless network card energy consumption). Each

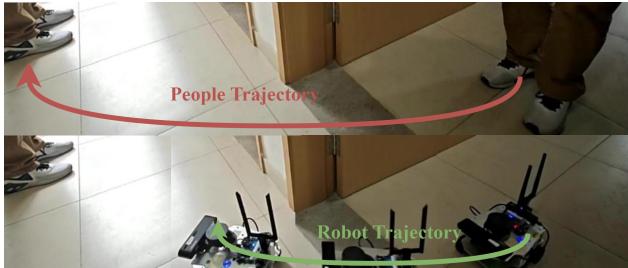


Figure 10: Kapao [54], a real-time people-tracking application on our four-wheeled robot with a CNN-based human keypoint detection model.

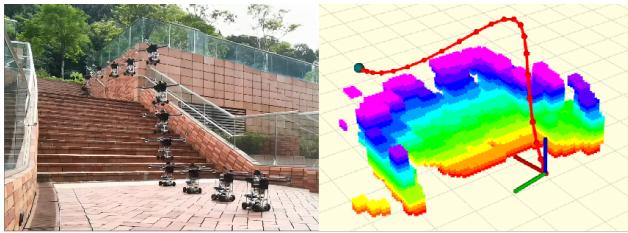


Figure 11: AGRNav [78], an autonomous navigation application on our air-ground robot with a CNN-based 3D semantic scene completion model.

Jetson Xavier NX is powered by a 21.6Wh battery, sustaining up to 1.6 hours of continuous model inference.

5.2 Experiment Setup

5.2.1 Task We evaluated two typical real-world robotic applications on our testbed: Kapao [54] (Fig 10) and AGRNav [78] (Fig 11). We also evaluated several models common to mobile devices with their implementation from Torchvision [52] on a larger scale to further corroborate our observations and findings: VGGNet [73], ConvNeXt [80], ResNet [75], DenseNet [32].

5.2.2 Emulation Environments We evaluated two real-world environments: indoors (robots move in our laboratory with desks and separators interfering with wireless signals) and outdoors (robots move in our campus garden with trees and bushes interfering with wireless signals, resulting in lower bandwidth). The corresponding bandwidths between the robot and the GPU server in indoor and outdoor scenarios are shown in Fig. 4.

5.2.3 Baselines To comprehensively evaluate the performance of Intra-DP, we conducted comparative experiments against several baseline approaches:

- **Device-only inference ("Device-only"):** A conventional setup where the entire model is deployed and executed on the mobile device.
- **Server-only inference ("Server-only"):** A cloud-based approach in which the full model runs on a GPU server. While both Device-only and Server-only represent extreme cases of layer partitioning, we evaluate them

separately to highlight the benefits of other baselines in terms of inference latency and energy efficiency.

- **DSCCS** [43]: A state-of-the-art layer partitioning method designed for inference acceleration. To ensure a fair comparison and eliminate the influence of parameter variations, we enhance DSCCS with Intra-DP’s adaptive control mechanism, allowing it to dynamically adjust to wireless network fluctuations.
- **SPSO-GA** [14]: An advanced layer partitioning method that optimizes energy consumption while satisfying timing constraints. We configure SPSO-GA with a 1 Hz deadline constraint, corresponding to the minimum frequency required for effective robotic motion control. As with DSCCS, we integrate Intra-DP’s adaptive control mechanism into SPSO-GA to allow real-time adaptation to network variations.

For consistency and accurate performance comparison, all systems are implemented without model compression, transmitting raw model activations to maintain accuracy. The Profiling and Scheduling Optimization stages of Intra-DP and all baselines run offline in advance.

6 Performance Evaluation

In this section, we evaluate the performance of Intra-DP from three research aspects: i) comprehensive comparisons with baseline systems to demonstrate the superiority of Intra-DP in terms of inference time and energy consumption for real-world mobile applications; ii) investigating the LOSS of Intra-DP through micro-event analysis; iii) sensitivity Studies to analyze system performance under varying network bandwidth variations, model structures, and equipment computational powers.

6.1 Superiority of Intra-DP

6.1.1 Inference Time Fig. 12 demonstrates the superior performance of Intra-DP compared to four baseline methods across various tasks and environments, achieving significant speedup in inference time (up to 50% for indoors and up to 48% for outdoors). Specifically, Intra-DP outperforms the closest baseline DSCCS by 8% to 26% indoors and 8% to 22% outdoors. These improvements primarily result from LOP, which enables parallel execution and overlaps computation with transmission across local operations within the same inference request, and LOSS, which optimizes scheduling under varying network conditions. Notably, all offloading-based methods, including server-only, two layer partitioning methods, and Intra-DP, exhibit greater standard deviations and longer inference times outdoors due to severe bandwidth fluctuations, as shown in Fig. 4. Although the performance gain is less pronounced on DenseNet, this is analyzed in our sensitivity study in Sec. 6.3.2. Additionally, a micro-event analysis in Sec. 6.2 further explains the efficiency of Intra-DP in inference.

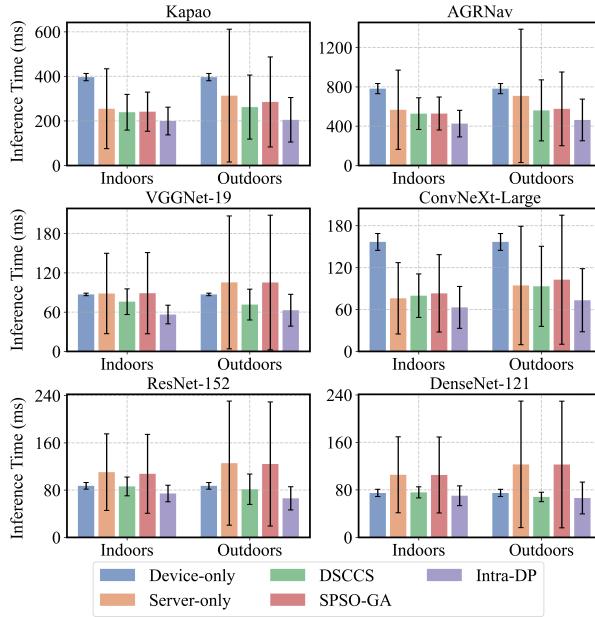


Figure 12: Inference time for different models across various environments and systems.

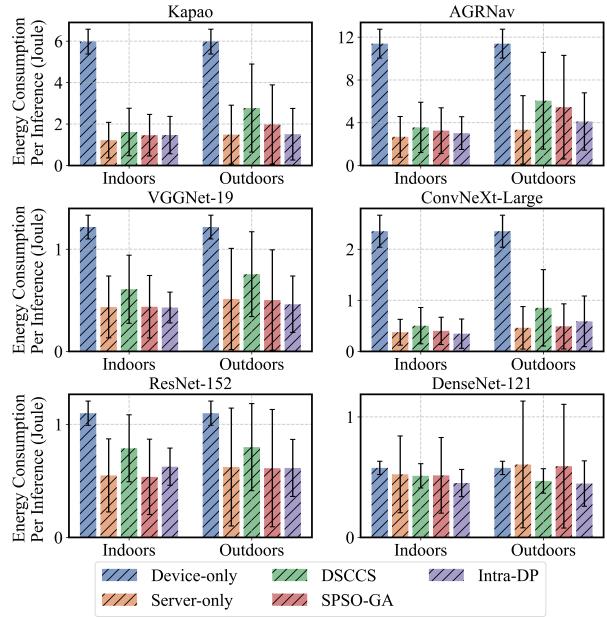


Figure 14: Energy consumption per inference request for different models across various environments and systems.

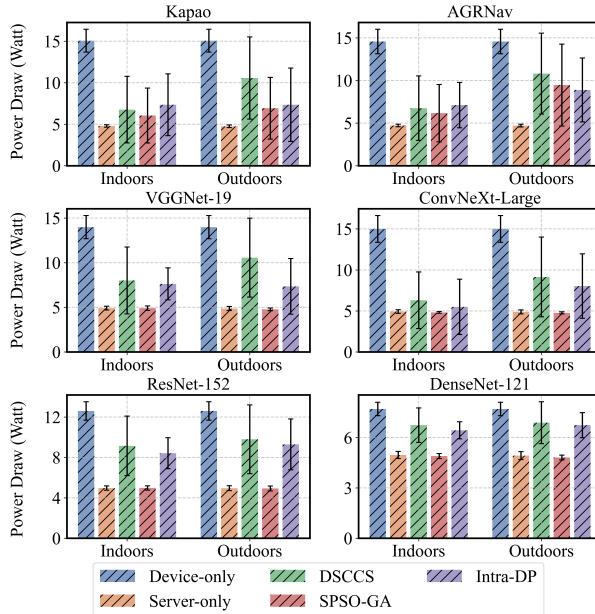


Figure 13: Power draw for different models across various environments and systems.

6.1.2 Energy Consumption Fig. 13 presents the power draw across different methods and scenarios. The device-only approach consumes the most energy due to the intensive computational load on robots, while the server-only approach achieves the lowest energy consumption by offloading all computations to the GPU server. Among the partial offloading methods, SPSO-GA demonstrates better energy

efficiency than DSCCS due to its energy-oriented optimization, whereas Intra-DP exhibits slightly higher energy consumption due to occasional re-computation of local operations. The power draw between Intra-DP and DSCCS remains nearly the same, indicating that the computation-communication overlap in Intra-DP does not introduce significant additional energy costs. Tab. 2 further supports this conclusion, showing that robots continue consuming 95% of their active power even when idle, mainly due to static energy consumption in components such as the CPU, GPU, and memory [37]. In contrast, the wireless network card consumes only 0.21W during transmission compared to 13.35W during computation.

Fig. 14 presents the energy consumption per inference request across different methods and scenarios. Although Intra-DP exhibits relatively higher power draw in Fig. 13, it achieves significantly lower energy consumption per inference request across all models and environments, reducing energy usage by up to 75% indoors and up to 72% outdoors due to its fast inference time. Notably, compared to the most energy-efficient server-only approach, Intra-DP increases energy consumption per inference request by at most 20% while reducing inference time by up to 42% and greatly reduced long tail delays.

6.2 Micro-Event Analysis

In this section, we present a detailed investigation of Intra-DP's superior inference speed through micro-event analysis, focusing on the effectiveness of LOSS compared to baseline methods.

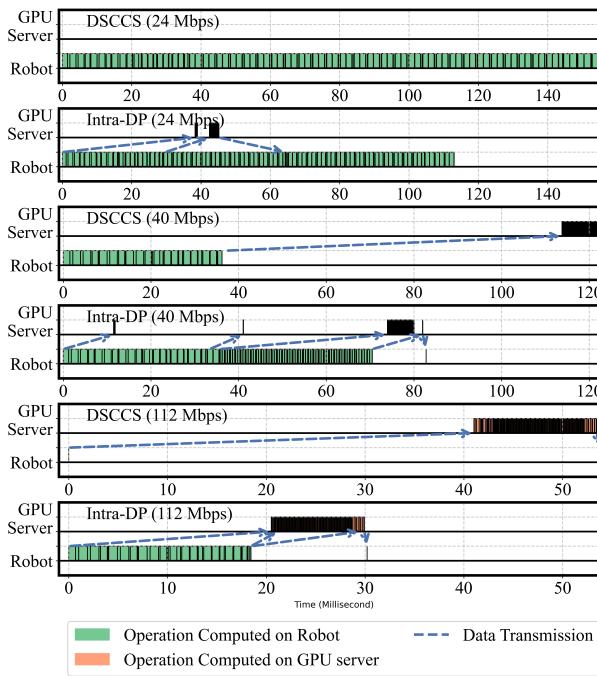


Figure 15: Snapshots of schedule plan of Intra-DP and baseline during runtime under various network bandwidth.

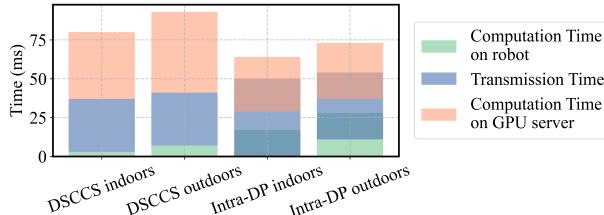


Figure 16: Breakdown of each phase of the inference process.

6.2.1 Detailed Schedule Plan To quantify the performance advantages of Intra-DP, we conducted a comparative analysis with DSCCS by recording real-time scheduling plans for ConvNeXt under varying bandwidth conditions, as shown in Fig. 15. The primary performance gain of Intra-DP stems from the parallel execution of local operations, enabling concurrent computation on the robot, data transmission, and computation on the GPU server. With the integration of Intra-DP’s adaptive control mechanism, DSCCS can dynamically select the optimal layer partitioning plan based on real-time network bandwidth. Under low-bandwidth conditions, DSCCS shifts more computation to the device, trading increased energy consumption for reduced tail latency. However, while DSCCS degrades to device-only, Intra-DP maintains its distributed execution capability by leveraging an expanded parallel scheduling space enabled by LOP, requiring less bandwidth for GPU server acceleration. Conversely, in high-bandwidth scenarios, DSCCS transitions to server-only, whereas Intra-DP leverages LOSS to optimize network and GPU server utilization for faster inference.

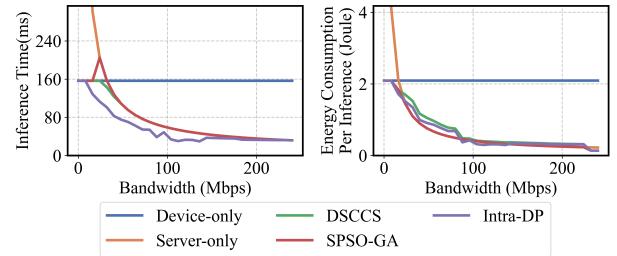


Figure 17: Performance comparison of Intra-DP and baselines under different network bandwidth conditions.

6.2.2 Breakdown Next, we provide a detailed breakdown of each phase of the inference process throughout the ConvNeXt experiment, as illustrated in Fig. 16. In DSCCS, transmission time accounts for up to 44.2% of the total inference time, underscoring the significant transmission bottlenecks encountered by existing layer partitioning methods, even when employing state-of-the-art strategies. Unlike layer partitioning methods, which execute each phase sequentially, Intra-DP enables the transmission phase, the robot computation phase, and the GPU server computation phase to run in parallel, resulting in faster inference times. Although Intra-DP introduces additional communication overhead due to the fine-grained transmission of local operators, it effectively reduces overall completion time through computation-communication overlap and early data transfer initiation, enabling it to outperform traditional layer partitioning methods, as demonstrated in Fig. 15.

6.3 Sensitivity Studies

6.3.1 Network Bandwidth To systematically evaluate Intra-DP’s performance under varying bandwidth conditions in MEC environments, we leveraged tc [9] over wired Ethernet to create controlled test scenarios, enabling comprehensive comparisons with baseline methods. As shown in Fig. 17, Intra-DP maintains superior performance across a wider range of network conditions, thanks to the expanded scheduling space enabled by LOP. When bandwidth is extremely low (near 0 Mbps), Intra-DP also degrades to device-only; however, its threshold bandwidth for degradation is significantly lower than that of DSCCS. Similarly, under extremely high bandwidth conditions, Intra-DP degrades to server-only, but its degradation threshold remains much higher than DSCCS. This highlights Intra-DP’s extensive parallel optimization space, enabling more efficient execution across diverse network conditions. Notably, the bandwidth thresholds at which layer partitioning methods and Intra-DP transition between device-only and server-only depend on model architecture and device computational power. Furthermore, the performance gain of Intra-DP in Fig. 12 and Fig. 14 is smaller than in Fig. 17 due to inaccurate bandwidth estimation during runtime.

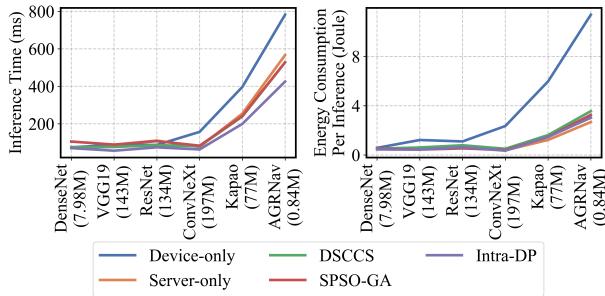


Figure 18: Performance comparison of Intra-DP and baselines with varying model structures.

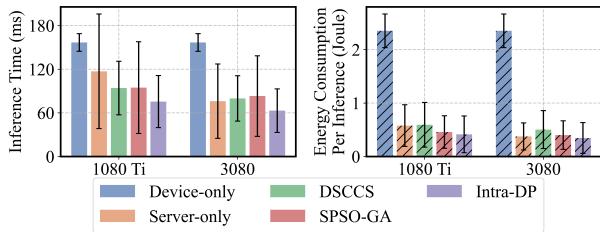


Figure 19: Performance comparison of Intra-DP and baselines on GPU servers with varying computational power.

6.3.2 Model structure As shown in Fig. 18, offloading methods (except device-only) achieved greater performance gains for models with higher computational demands but performed worse than device-only on DenseNet. This indicates that offloading is more beneficial for computationally intensive models, while models with lower computational demands may suffer from communication overhead, especially in bandwidth-constrained MEC systems. Furthermore, although Intra-DP consistently outperformed other baselines, its performance gains over them were relatively smaller for models with fewer parameters. This observation can be attributed to the fact that Intra-DP’s performance improvements are primarily achieved through the parallel execution of local operations, making its effectiveness dependent on the model’s size and structure. When a model has fewer parameters, the number of local operations available for parallel execution is reduced, thereby limiting Intra-DP’s optimization potential for enhancing performance.

6.3.3 Computational Power To assess Intra-DP’s performance under varying computational power disparities between the robot and the GPU server, we further evaluate Intra-DP using a GPU server equipped with an NVIDIA GTX 1080 Ti. As shown in Fig. 19, while offloading methods benefit from a greater power differential, Intra-DP achieves the most significant gains by optimizing GPU server utilization through parallel execution of local operations. It is also important to note that the mobile device used in our experiments has substantially higher computational power than typical mobile devices, such as smartphones, as illustrated in Fig. 2a.

7 Related work and discussion

Limited bandwidth. Due to hardware limitations, we evaluated Intra-DP’s performance only on commonly available Wi-Fi networks in robotic environments, rather than a broader set of wireless technologies such as 6G [12] or WiMAX [4]. While different wireless networks vary in throughput and range due to distinct transmission protocols, they all suffer from weak connections caused by intermittent jitter and packet loss [47], leading to bandwidth fluctuations in practice (Fig. 4). In these conditions, Intra-DP proves beneficial. When GPU servers are deployed in commercial cloud environments, network congestion and routing inefficiencies further restrict available bandwidth [60], making Intra-DP even more advantageous. Furthermore, as models scale and GPU computational power increases, Intra-DP’s advantage continues to grow, further highlighting its relevance.

Inference Request Scheduling. It schedules multiple DNN inference requests to optimize overall latency and energy consumption while leveraging existing collaborative inference methods for individual executions. Various decision algorithms, such as request batching [94], urgency-based prioritization [45, 51], and deep reinforcement learning-based control [6, 19, 20], are employed to determine execution locations and timing. Intra-DP enhances these approaches by introducing a higher-performance collaborative inference method for MEC, and these scheduling strategies can be seamlessly integrated into Intra-DP.

Model Compression. Quantization and model distillation are two most common model compression techniques for mobile devices. Quantization [17, 24, 27] reduces precision of model weights and activations to lower computation costs, while model distillation [28, 46, 79] trains a smaller model to mimic a larger one with fewer resources. Unlike these methods, which trade accuracy for efficiency, collaborative inference accelerates computation by intelligently distributing workloads without compromising accuracy. Building on the significant performance gains already achieved by Intra-DP, our future work will explore how sacrificing some accuracy through techniques such as quantization or early-exit policies [39] can further enhance its efficiency.

8 Conclusion

In this paper, we have proposed Intra-DP, a high-performance collaborative inference system optimized for MEC networks. By leveraging LOP for fine-grained computation partitioning and LOSS for optimized scheduling, Intra-DP reduces transmission overhead by overlapping computation with communication. We envision that the fast and energy-efficient inference of Intra-DP will facilitate the deployment of diverse robotic tasks on real-world mobile devices, promoting the broader adoption of advanced machine learning techniques in mobile applications.

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