Multi-Objective Hardware-Mapping Co-Optimisation for Multi-Tenant DNN Accelerators

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Abstract—To meet the ever-increasing computation demand from emerging workloads, a scalable design paradigm combines multiple Deep Neural Network (DNN) accelerators to build a large multi-accelerator system. They are mainly proposed for data centers, where workload varies across vision, language, recommendation, etc. Existing works independently explore their hardware configuration and mapping strategies due to the extremely large cross-coupled design space. However, hardware and mapping are interdependent and, if not explored together, may lead to sub-optimal performance when workload changes. Moreover, even though a data center accelerator has multiple objectives, almost all the existing works prefer aggregating them into one (mono-objective). But aggregation does not help if the objectives are conflicting, as improving one will worsen the other.

This work proposes MOHaM, a multi-objective hardware-mapping co-optimisation framework for multi-tenant DNN accelerators. Specifically, given an application model and a library of heterogeneous, parameterised and reconfigurable sub-accelerator templates, MOHaM returns a Pareto-optimal set of multi-accelerator systems with an optimal schedule for each one of them to minimise the overall system latency, energy and area. MOHaM is evaluated for diverse workload scenarios with state-of-the-art sub-accelerators. The Pareto-optimal set of competitive design choices enables selecting the best one as per the requirement.

I. INTRODUCTION

Deep Neural Network (DNN) accelerators drives the era of Domain-Specific Architectures (DSAs). From edge [2] to the cloud [5], they are ubiquitous to enable performance improvement for different workloads. To meet the ever-increasing computation demand from emerging workloads, a scalable design paradigm combines multiple sub-accelerators to build a large accelerator system. Existing works have explored the combination of both, homogeneous as well as heterogeneous sub-accelerators [50][5][4][8][12][18][33][35][28]. Conceptual view of a multi-accelerator system is shown in Figure 1.

Due to limited area and power budget at the edge, multi-accelerator systems are usually employed in the cloud, i.e., data centers. Two of the most important factors deciding a DNN accelerator performance are its hardware configuration and mapping strategy. Their design spaces are extremely large and hence are often explored independently [24][23][53][26]. With multiple sub-accelerators, these design spaces are only becoming larger in multi-accelerator systems. For example, MAGMA [28] reported the design space of mapping alone to be of size $O(10^8)$. However, hardware and mapping are interdependent and, if not explored together, may lead to sub-optimal performance when workload changes [32]. As multi-accelerator systems are proposed for data centers, where workload varies across vision, language, recommendation, etc., each with different variants of DNNs [7][41], hardware-mapping co-optimisation is very important and timely. Some works on co-optimisation are available [29][48][55][57], but they do not discuss multi-accelerator systems due to the obvious challenge of huge cross-coupled search space. Table 1 presents the existing works on multi-accelerator systems, where Planaria [18] and Herald [33] are the only ones attempting co-optimisation. Nevertheless, Planaria lacks dataflow flexibility, and both of them rely on heuristic-based (manually-designed) decision-making. This limits their scalability towards diverse sub-accelerators and emerging workloads.

A primary enabler of scalability in data centers is multi-tenancy, where different DNN models are simultaneously executed on an accelerator. Multi-tenancy trivially becomes a key aspect in multi-accelerator systems as they house sub-accelerators supporting diverse DNNs. As given in Table 1, quite a few existing works have support for multi-tenancy. However, except MAGMA [28], which uses Genetic Algorithm (GA), all employed manually-designed support, which may limit accelerator utilisation and deployment benefits.

Designing an accelerator for data center often has more than one objective, like a subset of latency (delay), throughput, energy, area, temperature, etc. A convenient way of exploration preferred in the existing works is the aggregation of multiple objectives into one (mono-objective), say, Energy-Delay-Product (EDP). However, a chosen group of objectives might be conflicting with one another; in which case, aggregation does not help. Hence, a multi-objective exploration is necessary for identifying multiple design points to select the most suitable one according to the requirement. MEDEA [48]
Table 1: Comparison of existing works on multi-accelerator systems based on design space exploration of hardware, mapping, multi-tenency (Mul-Ten) and multi-objective (Mul-Obj).

| Work      | Hardware | Mapping | Mul-Ten | Mul-Obj |
|-----------|----------|---------|---------|---------|
| Simba [50]| ❌       | ✓       | ❌       | ❌       |
| TPUv4 [5] | ✓        | ✓       | ❌       | ❌       |
| CS-2 [4]  | ❌       | ✓       | ❌       | ❌       |
| AI-MT [8] | ❌       | ✓       | ❌       | ❌       |
| PREMA [12]| ❌       | ✓       | ❌       | ❌       |
| Planaria [18]| ✓ | ✓ | ✓ | ❌ |
| Herald [33]| ✓ | ✓ | ✓ | ✓ |
| VELTAIR [35]| ✓ | ✓ | ✓ | ✓ |
| MAGMA [28]| ❌ | ✓ | ✓ | ✓ |
| MOHaM     | ✓        | ✓       | ✓       | ✓       |

is the only work focusing on true multi-objective exploration of DNN accelerators. As given in Table 1, none of the existing multi-accelerator systems have explored this direction.

This work proposes a Multi-Objective Hardware-Mapping co-optimisation framework (MOHaM) for multi-tenant DNN accelerators\(^1\). It is the first attempt at simultaneous exploration of hardware configuration and mapping strategy for multi-tenancy with multiple distinct objectives. Specifically, the proposed work makes the following major contributions:

1) Given an application model and a library of heterogeneous, parameterised and reconfigurable sub-accelerator templates, MOHaM returns a Pareto-optimal set of multi-accelerator systems with an optimal schedule for each one of them to minimise latency, energy and area.

2) To search the enormous design space, MOHaM extends the NGSA-II [14] multi-objective GA with several custom genetic operators specific to the problem definition. This improves the search efficiency and makes MOHaM much faster than the standard optimisation techniques.

3) Experimental evaluation with diverse workload scenarios and state-of-the-art sub-accelerators show that MOHaM is able to generate competitive design points considering all the objectives. To the best of the author’s knowledge, this is the first work offering hardware-mapping co-optimisation, support for multi-tenancy and multi-objective exploration, all in a single framework.

II. BACKGROUND

A. Multi-Accelerator System

As shown in Figure 1, it is a coming together of multiple DNN accelerators (called sub-accelerators in the bigger context). To ensure scalability, this work considers a Multi-Chip-Module (MCM) based multi-accelerator system, like Simba [50], where each of the Sub-Accelerators (SAs) is a chiplet connected by a Network-on-Package (NoP). However, unlike Simba, which combines homogeneous chiplets, the multi-accelerator system in this work considers heterogeneity to support diverse DNN models and emerging workloads.

1MOHaM will be available on GitHub after acceptance.

1) Sub-Accelerator Architecture: Each SA is a standard DNN accelerator with an array of Processing Elements (PEs) and a shared Global Buffer (GB) [9]. Each PE houses one or more Multiply-Accumulate (MAC) units to compute partial sums and a Local Buffer (LB) to store them. GB collects weights and activations from the memory (HBM/DRAM) through the NoP and distributes them to the LBs through the Network-on-Chip (NoC). Similarly, outputs are written from LB to GB and then to memory through NoC and NoP, respectively. Existing literature has many promising DNN accelerators that could be used as an SA chiplet to build a multi-accelerator system [43][50][10][3][6][40][20][15].

2) DNN Models: Data center workloads mainly revolve around vision, language and recommendation-based DNN models [7][46][41]. Based on the shape and operation, different layers of a DNN model may have a specific dataflow preference. However, most of the SAs are usually optimised for some specific layers with a fixed dataflow [33]. Figure 2a shows how the normalised EDP varies when the same DNN model is run on different SAs. Here, three dominant layers, Convolution CONV_0 and CONV_33, and Fully Connected FC_2/31 from the ResNet50 DNN model [21] are considered. These layers are individually run on row-stationary (Eye-riss [9]), weight-stationary (Simba [50]) and output-stationary (ShiDianNao [15]) SAs. Similar observations are available in the literature [33][57][39][32][34] but the objective here is to advocate for flexible accelerators. A multi-accelerator system for data centers should consider heterogeneous SAs for dataflow flexibility to diverse and emerging DNN models.

B. Hardware-Mapping Co-Optimisation

A typical hardware-mapping co-optimisation framework takes as input, a target DNN model, an optimisation objective (e.g. latency) and the resource constraints (e.g. area). It returns as output a hardware configuration with the optimal instances of resources and an optimal mapping strategy to run the DNN model on the accelerator. This co-optimisation can be used at design-time to build a more efficient accelerator. However, the search space is extremely large as it is the cross-product of hardware and mapping. For example, DiGamma [29] recently reported a design space as large as $O(10^{36})$, and that is only for a single accelerator. The same space for a multi-accelerator system could reach up to $O(10^{55})$ with just 4 ResNet50-like DNN models and 16 SAs, by using equation (1) through (5).

III. MOTIVATION

Figure 2b and 2c shows a conceptual representation of the design space exploration with three optimisation objectives, energy (x-axis), latency (y-axis) and area (size of the design points). Figure 2b shows design points with hardware-only optimisation (blue), mapping-only optimisation (red), and co-optimisation (yellow). The blue design points, in general, have lower energy and area as a result of optimal hardware resources but relatively higher latency due to fixed mapping strategy. On the contrary, the red design points have lower latency as a result of optimal mapping strategy but a fixed area...
The yellow design points do not follow a fixed pattern and provide some interesting options. For example, with a small increase in area due to additional hardware resources allows a better mapping strategy (co-optimisation). Design point B shows that an area slightly lower than A has no impact on latency but increases energy. Design point C shows that a small compromise on latency can significantly improve energy as well as area. In this way, co-optimisation may offer competitive design points.

The conventional way of aggregating multiple optimisation objectives into one (mono-objective) is shown in blue in Figure 2c. This practice offers a single design point which might not be optimal if objectives conflict. For example, due to the chosen memory hierarchy, if the system bandwidth is insufficient to feed enough data into the compute (MAC) units, they remain underutilised. In such a scenario, two mapping strategies may output identical latency but varying hardware resource utilisation, hence different energy and area. Similarly, it is possible to either access an enlarged on-chip buffer or the next-level buffer (memory) within the same energy budget. In such a scenario, even two hardware-mapping co-optimisations may output identical energy but different latency and area. These scenarios can be expressed as a set of non-dominating design points (multi-objective), as shown in red in Figure 2c. These Pareto-optimal set of distinct multi-objective solutions allow simultaneously exploring accelerator designs with varying requirements. To give a specific use case, suppose the accelerator needs to be deployed for remote robotic surgery with hard real-time constraints. Then design point A with the lowest latency is preferred without bothering about energy and area. In another use case, energy and area are paramount when the accelerator is deployed for consumer wearables like smart glasses. Design point B could be the preferred choice then. These factors motivated the MOHaM framework to target multi-objective co-optimisation in multi-accelerator systems.

IV. PROBLEM FORMULATION

This section first defines the inputs and outputs of the proposed MOHaM framework, then formulates the exploration problem and finally computes the size of the search space. Most of the acronyms/abbreviations and terms used to explain the MOHaM framework are presented in Table 2 for reference.

A. Definitions

Definition 1. A DNN model is a directed graph $DNN = G(L, D)$ where $L$ is the set of layers and $D$ is the set of dependencies between layers. For example, a layer dependency $d = (l_i, l_j) \in D$, $l_i, l_j \in L$ states that layer $l_j$ can be executed only after layer $l_i$. A layer $l \in L$ has a set of properties like, the type of layer (e.g., CONV_0, FC_121), the shape of input activation and weights (e.g., width, height, channels), etc.

Definition 2. An Application Model, $AM(L, D)$, is a set of DNN models $\{DNN_i(L_i, D_i)\}$ where $L = \cup_i L_i$ and $D = \cup_i D_i$. The DNN models within an AM are assumed to be independent of each other and thus can be executed in parallel.

For example, $AM$ for an Augmented Reality (AR) application will have multiple DNN models, each with a specific task like object detection, gesture identification, depth estimation, etc. Figure 3(a) shows an $AM$ formed by three $DNN$ models.

Definition 3. A Sub-Accelerator Template, $SAT$, is a parameterised and reconfigurable DNN accelerator supporting different hardware configurations as well as mapping strategies.

For example, a modifiable Simba chiplet [50] could be a $SAT$.

Definition 4. A Sub-Accelerator Instance, $SAI$, is an instance of a $SAT$ configured with specific values to its parameters.

For example, Simba $SAT$ becomes a Simba $SAI$ when its configurable parameters are given values, like, 128 PEs, 256 KiB GB, 32 KiB LB, weight-stationary dataflow, etc.

Definition 5. A Network-on-Package (NoP) is a directed graph $NoP = G(T, C)$ where $T$ is the set of tiles and $C$ is the set of communication links. A tile $t \in T$ hosts a $SAI$ and has a router to communicate with other tiles in the package.

Definition 6. A Multi-Accelerator System, $MAS$, is a tuple $\langle SSAI, NoP, SMI, PF \rangle$ where $SSAI$ is the set of heterogeneous $SAI$ chiplets and $SMI$ is the set of Memory Interfaces (MIs) for external HBMs/DRAMs, all connected together by the $NoP$. $PF$ is the placement function such that for a $SAI \in SSAI$ or a $MI \in SMI$, it returns the hosting tile.

Figure 3(d) shows a $MAS$ created by eight $SAIs$ and an external memory, interconnected by an $NoP$. The $SAIs$ are instances of four parameterised and reconfigurable $SAT$s, as shown in Figure 3(b). For example, $SAI0.0$, $SAI0.1$ and $SAI0.2$ are three different instances of $SAI0$ and so on.
Definition 7. A Schedule, \( S(MAS, AM) \), for an \( AM(L, D) \) is a directed bipartite graph \( S = G(L, SSAI, D^+, M) \) where \( D^+ \supseteq D \) is the set of edges that models the dependencies among layers at the application level. \( M \) is the set of edges that maps a layer \( l \in L \) into a chiplet \( SAI \in SSAI \).

For example, Figure 3(e) shows a schedule for the \( AM \) in Figure 3(a) and the \( MAS \) in Figure 3(d). \( D^+ \) and \( M \) are shown by black and red edges, respectively. \( D^+ \) might contain dependencies like \( d' \) and \( d'' \) that are not present in \( D \). Both, \( L.0.3 \) of \( DNN0 \) and \( L.2.2 \) of \( DNN2 \) are mapped onto \( SAT3.0 \). \( d' \) defines the execution order and dictates that \( L.0.3 \) be run only after \( L.2.2 \). Similarly, \( d'' \) dictates \( L.0.3 \) be run first.

B. Problem Formulation

Given an application model, \( AM \), and a library of heterogeneous, parameterised and reconfigurable sub-accelerator templates, \( SAT \)'s, find the Pareto-optimal set of multi-accelerator systems, \( MAS \), and an optimal schedule, \( S \), for each one of them to minimise the overall system latency, energy and area.

C. Search Space

Search for the Pareto-optimal set of solutions involves a design space exploration that is an \( n \)-fold Cartesian product of SA hardware space, SA mapping space, layer-to-SA mapping space, SA-to-tile mapping space, and schedule space.

Major SA hardware includes PEs, MACs, GB, LB, etc. For each \( SAT \), let \( np \) be the number of free parameters and \( v \) be the number of configurable values a free parameter can have. Then for the entire \( SSAI \), the size of SA hardware space is:

\[
v^{np} \times |SSAI| \tag{1}
\]

DNN models are represented by tensors, and their computation involves multiple loops. A dataflow defines the loop order, parallelism and clustering, and is usually expressed in a loop-nest form \([9][57][33][29]\). Mapping determines tiling, i.e. how tensors are sliced, stored and transferred across the memory hierarchy, and uses a dataflow to map a layer \( l \) into an \( SAI \). Let \( nl \) be the depth of loop-nest, \( C \) and \( K \) be the input and output channels, \( Y \) and \( X \) be the width and height of input activation, and \( R \) and \( S \) be the width and height of weights. For \( AM(L, D) \), the size of SA mapping space is:

\[
nl! \times 2^{nl} \times (C \times K \times Y \times X \times R \times S) \times |L| \tag{2}
\]

where, \( nl! \) is the loop order, \( 2^{nl} \) is for parallelism and clustering, and \((C \times K \times Y \times X \times R \times S)\) is for the tiling.

As each layer of the \( AM(L, D) \) can be mapped onto each of the \( SSAI \)'s, the size of layer-to-SA mapping space is:

\[
|L| \times |SSAI| \tag{3}
\]

Each \( SAI \) can be mapped onto a tile \( t \) of the NoP. Let the number of tiles corresponds to the number of SA instances (i.e., \(|T| \equiv |SSAI|\)). Then the size of SA-to-tile mapping space is the permutation of SAs in different tiles, which is:

\[
|SSAI|! \tag{4}
\]

Finally, let each DNN model of an \( AM(L, D) \) has \( l \) layers, and none are parallel. If the \( AM(L, D) \) is formed by \( nd \) parallel DNN models, the size of the schedule space is:

\[
(nd! \times l) \times |SSAI| \tag{5}
\]

The complete search space is the product of equation (1) through (5), and changes factorially with the number of DNN models, SAs and the depth of loop-nest in the \( AM(L, D) \).

V. THE MOHAM FRAMEWORK

To search the enormous design space, the proposed MOHaM framework adopts a two-step approach, layer mapping and global scheduling. In the first step, each layer of the \( AM(L, D) \) is mapped onto each of the \( SAT \)'s available in the input library. Then the Pareto-optimal set of mappings found for each layer is used in the second step to search the global scheduling. MOHaM is written in C++ and uses the Timeloop [39] + Accelergy [54] framework for realising both the steps. Algorithm 1 presents a high-level flow of MOHaM, and the following sub-sections describe its working in detail.

A. Layer Mapper

Let \( SSAT \) be the set of \( SAT \)'s available in the input library. As per equation (3), if each layer of the \( AM(L, D) \) is mapped onto each of the \( SAT \)'s, the search space can be as large as \(|L| \times |SSAT|\). However, two layers, \( l_i, l_j \in L \) can be instances of the same workload, i.e., have the same problem dimensions. Hence, in an attempt to reduce the layer mapping search space, MOHaM only maps the unique layers to each of the \( SAT \)'s.

Let \( M_{l,f,i} \) be a mapping for a layer \( l \in L \) in an SA template \( f \in SSAT \). \( M_{l,f,i} \) is a choice of a specific tiling, loop ordering, parallelism and clustering in \( f \). Now, let \( MF_{l,f} \) be the Pareto-optimal set of mappings with respect to latency, energy and area for \( l \) in \( f \). \( MF_{l,f} \) can be represented by:

\[
MF_{l,f} = \{ M_{l,f,i} \mid i = 0, \ldots, (m_{l,f} - 1) \} \tag{6}
\]
Algorithm 1 MOHaM High-Level Flow

```
procedure LAYERMAPPER(AM, SSAT)
    MG ← {}
    for layer in UNIQLAYERS(AM) do
        ML ← {}
        for arch in SSAT do
            MF ← RUNMEDEA(layer, arch)
            ML.ADD(MF)
        end for
        MG. ADD(ML)
    end for
    return MG
end procedure

procedure GLOBALSCHEDULER(AM, SSAT, MG)
    PP ← INITIALPOPULATION()
    for g ← 1 to G do
        OP ← APPLYCROSSOVEROPERATORS(PP)
        OP. APPLYMUTATIONOPERATORS(OP)
        OP. EVALUATE()
        MP ← FASTNONDOMINATEDSORTING(PP, OP)
        OP ← SURVIVAL(MP)
    end for
    return PP. GETPARETOEFFICIENTINDIVIDUALS()
end procedure

procedure MOHAM(AM, SSAT)
    MG ← LAYERMAPPER(AM, SSAT)
    ST ← GLOBALSCHEDULER(AM, SSAT, MG)
    return ST  
end procedure
```

where, $m_{l,f}$ is the number of Pareto-optimal mappings. Now, let $M_{l}$ be the Pareto-optimal set of mappings for $l$ in all the input SA templates of $SSAT$. $M_{l}$ can be represented by:

$$M_{l} = \{ MF_{l,f} | f = 0, \ldots, (F - 1) \}$$

where, $F$ is the number of input SA templates, i.e., $|SSAT|$. Finally, let $MG$ be the Pareto-optimal set of mappings for all the layers of $AM(L, D)$ in all the input SA templates of $SSAT$. $MG$ can be represented by:

$$MG = \{ M_{l} | l = 0, \ldots, (L - 1) \}$$

where, $L$ is the number of layers in the $AM(L, D)$. To obtain the Pareto-optimal sets in equation (6) through (8), MOHaM leverage state-of-the-art MEDEA [48] infrastructure. For the optimisation objectives, latency, energy and area, MEDEA searches for a Pareto-optimal set of mappings for a layer on a $SAI$ employing a GA with custom operators. MEDEA can only map a single layer on a single accelerator, while MOHaM has the capability for multi-DNN models and multi-accelerator systems. MOHaM decides $SAI$s, their hardware parameters, and schedule layers with appropriate mappings and $SAIs$. Hence, as given in Algorithm 1, MEDEA is just one component of MOHaM’s complex multi-objective search.

B. Global Scheduler

It is based on one of the most widely accepted multi-objective GA, NGSA-II [14]. It has five major phases, sampling, selection, crossover, mutation and survival. The scheduler uses the original selection and survival phases of the NGSA-II. However, multiple custom genetic operators are implemented for problem-specific crossover and mutation, and also for increasing the sampling efficiency to find better individuals in less time. The global scheduler of MOHaM
returns a Pareto-optimal set of \( MAS \) and an optimal \( S \) for each one of them with minimum latency, energy and area.

1) Chromosome Encoding: One of the most fundamental and important steps in employing a GA is to define an encoding for the individuals in the population. MOHaM requires this encoding to represent, (a) mapping strategy of each layer, (b) \( SAI \) of each layer, (c) execution sequence of layers in the \( AM(L, D) \), (d) SA template of each \( SAI \), and (e) NoP tile of each \( SAI \). Hence, the global scheduler uses a two-part chromosome, as shown in Figure 4. The two parts are:

- **Software Genome**: It encodes the layers of the \( AM(L, D) \). It is an array of genes, where each gene denotes a layer. Each gene is a tuple \( \langle LI, MI, SAI \rangle \) where \( LI \) is the layer identifier, \( MI \) is the mapping identifier, and \( SAI \) is the SA instance the layer will be executed. The order of the genes is a topological sorting of the layers using Kahn’s algorithm [25] and represents the temporal sequence in which the layers will be executed. The number of genes is equal to the number of layers in the \( AM(L, D) \) and is fixed for chromosomes.

- **Hardware Genome**: It encodes the instances of the \( SSAT \). It is an array of genes, where each gene denotes a SA instance. Each gene is a tuple \( \langle SAI, SAT \rangle \) where \( SAI \) is the SA instance and \( SAT \) is the template identifier. The order of the genes represents position of the \( SAI \) hosting tile in the 2D Mesh NoP. The number of genes is equal to the number of SA instances and varies between 1 and maximum NoP tiles across chromosomes.

2) Custom Genetic Operators: Each chromosome must respect certain constraints for it to represent a valid individual. For example, the topological sorting of layers in the software genome must be valid. It has to be a traversal where a layer is placed only after all its dependencies. Similarly, the \( SAI \) of a layer must refer to one of the encoded genes in the hardware genome. Furthermore, the \( MI \) of a layer must refer to one of the mappings in the \( MFL_{li} \). In order to improve the search efficiency, a set of custom genetic operators are implemented that considers these constraints. The operators either avoid generating invalid combinations or use compensation mechanisms. Operators targeting the topological sorting in the software genome are similar to [56]. MOHaM-specific genetic operators are shown in Figure 5 and are described here:

- **Scheduling Crossover**: It combines the topological sorting of the parent chromosomes, as shown in Figure 5(a). It generates offspring by taking the first part of one of the parents, i.e., all the genes before the crossover point, and appending all the unique genes from the other parent.

- **Scheduling Mutation**: It mutates the topological sorting of a chromosome, as shown in Figure 5(b). Let \( l_i \) be a random gene (layer). Let \( l_j \) be the nearest layer in the traversal that is dependent on \( l_i \). Let \( l_k \) be a random gene between \( l_i \) and \( l_j \). If all the layers \( l_k \) has a dependency lie before \( l_i \) in the traversal, their position can be swapped.

- **Mapping Mutation**: It modifies the \( MI \) of a random layer \( l_i \), to mutate a chromosome, as shown in Figure 5(c). The possible mappings for a layer will be in the \( ML_{l_i,f} \). One of those mappings is assigned to the \( l_i \) for mutation.

- **Mapping Crossover**: It combines the mappings of the parent chromosomes, as shown in Figure 5(d). It generates offspring by taking layer mappings from the first part of one of the parents, i.e., from all the genes before the crossover point, and the remaining ones from the other parent. However, the mapping for a layer (gene) might not be valid if the SA instance is of a different template. In that case, a compensation mechanism called Mapping Transform is applied to find the most similar one among all the possible mappings for the layer in that SA instance.

- **SA Crossover**: It swaps a random SA instance \( s_i \) between the parent chromosomes, as shown in Figure 5(e). If both parents \( A \) and \( B \) have an instance with the same identifier \( s_i \), they are swapped and two offspring are generated. If \( s_i \) of \( A \) and \( s_i \) of \( B \) are of different SA templates, all the mappings from both of their layers undergo mapping transformation. If \( s_i \) is only in one of the parents, it is added to the other parent with all its assigned layers. Then only one offspring is generated.

- **SA Splitting Mutation**: It reduces the load in a random SA instance \( s_i \) to mutate a chromosome, as shown in Figure 5(f). Another instance \( s_j \) of the same SA template is appended to the hardware genome. Thereafter, half of the layers currently assigned to \( s_i \) are randomly chosen and assigned to \( s_j \). The goal is to increase parallelisation.

- **SA Merging Mutation**: It increases the load in a random SA instance \( s_i \) to mutate a chromosome, as shown in Figure 5(g). Another instance \( s_j \) of different SA templates, all the mappings of the imported layers undergo mapping transformation. The goal is to reduce chip area cost with reduced SAs.

- **SA Position Mutation**: It swaps the position of two SA instance \( s_i \) hosting tiles in the 2D Mesh NoP, as shown in Figure 5(h). The goal is to find a configuration where the system bandwidth is distributed among the NoP links and memory interfaces in a way to avoid bottlenecks (stalls).

- **SA Template Mutation**: It modifies the \( SAT \) of a ran-
dom SA instance $s_i$ to mutate a chromosome, as shown in Figure 5(i). All the mappings from different layers to the mutated instance $s_i$ undergo mapping transformation.

- **Layer Assignment Mutation:** It modifies the $SAI$ of a random layer $l_i$ to mutate a chromosome, as shown in Figure 5(j). If the modified $SAI$ is an instance of a different SA template, mapping transformation is applied.

C. Objectives Evaluation

Three objective metrics are evaluated for each individual: latency, energy, and area. Their values are determined by both, hardware and software genomes of the individual’s chromosome. For example, increasing the number of SA instances decreases latency but increases area. Similarly, the mapping strategy for each layer of the $AM(L, D)$, and the SA templates affect all three metrics. The translation from chromosome encoding to target metrics is not through analytical models. Timeloop [39] + Accelergy [54] framework only allows the simulation of a single layer on a single accelerator instance. Hence, it is repeatedly run for multiple layers and SA instances and the results are combined and processed by MOHaM.

The translation begins from the hardware genome. Each of its genes is converted into a SA instance of the appropriate $SAT$. At this point, the buffer sizes and instances of each $SAT$ is unknown. Then software genomes are examined to identify which mappings are used for each gene (layer). Now all the free parameters, including number of PEs, size of buffers, etc. are set to maximum required by the mappings for all the layers assigned to an SA instance. So, each of the instances can execute all the assigned layers, and the area is estimated.

As each of the mappings has a corresponding energy, summing them for all the layers could provide the total estimation. However, the energy for reads and writes in buffers depends on their sizes. Hence, energy for each mapping must be estimated based on the updated values of the free parameters in the corresponding SA instance. Their sum is the total energy.

Latency is estimated using the topological sorting encoded in the software genome. Each of its genes (layers) is read sequentially and mapped on the assigned SA instances. This traversal guarantees that all the dependencies of a layer are already scheduled before its turn comes. Each layer has a start and end time and the total latency is estimated based on the latest end time among all the layers. However, this is true only when there are no communication or memory bottlenecks.

1) **Communication Modeling:** As shown in Figure 3(d), MOHaM assumes that the $SAIs$ and memory are interconnected by a 2D Mesh NoP. It is implemented via on-package links using a passive silicon interposer. It employs efficient intra-package signalling circuits using Ground-Reference Signaling (GRS) technology. Specifically, each chiplet is equipped with eight chiplet-to-chiplet GRS transceivers; four transmitters and four receivers. A transceiver has four data lanes, each providing 4 GB/s, thus a total peak chiplet bandwidth of 4 * 4 GB/s = 16 GB/s and energy of 0.82 pJ/bit. MOHaM also assumes that the entry points of NoP are Memory Interfaces (MIs), which connect memory banks. $SAIs$ reads and writes in their nearest MIs. Some CPU processing happens between layer execution (e.g. tensor reordering) and the output is stored in the nearest memory bank of the $SAI$ executing the next layer. Depending on their position in the NoP, multiple $SAIs$ could be assigned the same MI, thus competing for the shared link. If a time segment has parallel execution of layers and the required bandwidth is below the bottleneck, it undergoes temporal dilation. However, it only concerns the $SAIs$ sharing the same MI and requires compensating the start times of all the subsequent layers to keep respecting dependencies. After re-evaluating the stalled time segments, the latest end time among all the layers becomes the estimated total latency.

2) **Convergence Criterion:** The MOHaM framework supports a GA stopping criterion based on the density of the non-dominated solutions presented in [47]. Alternatively, simulating for a fixed number of generations can also be configured.
Table 3: Multi-tenant workload scenarios

| # | Workload | Domain         | DNN Model            |
|---|----------|----------------|----------------------|
| A | Mobile   | Image Classification | MobileNetV3L          |
|   |          | Image Segmentation  | DeepLabV3+ MN2        |
|   |          | Language Processing | Mobile-BERT           |
| B | Edge     | Image Classification | ResNet50             |
|   |          | Object Detection    | SSD-ResNet34          |
|   |          | Language Processing | BERT-Large           |
| C | AR/VR    | Image Classification | ResNet50             |
|   |          | Object Detection    | SSD-MobileNetV1       |
|   |          |                     | YOLOv3                |
|   |          | Image Segmentation  | UNet                  |
| D | Data Center | Image Classification | GoogleNet           |
|   |          | Object Detection    | YOLOv3                |
|   |          | Language Processing | BERT-Large           |
|   |          | Recommendation      | DLRM                  |

VI. Evaluation

A. Methodology

1) DNN Models and Workloads: Inspired by the popular MLPerf benchmark suite [45][36], multiple DNN models from major application domains like vision, language and recommendation are considered. MOHaM is proposed for design-space exploration of multi-accelerator systems where the application domains are known/guessed apriori. Hence, it is evaluated against mobile, edge, and AR/VR workloads. While these devices do not deploy multi-accelerator systems directly, MOHaM assumes that their heavy workloads are offloaded in the cloud, i.e., data centers. MOHaM is also evaluated against a data center workload to show its effectiveness if the application domains can be guessed. Table 3 presents the workload scenarios along with their DNN models. MOHaM takes them as inputs in the ONNX [1] interoperable format.

2) Sub-Accelerator Templates: The following state-of-the-art accelerators constitute the SAT library in MOHaM:

- Eyeriss [9]: Row-stationary dataflow
- Simba [50]: Weight-stationary dataflow
- ShiDianNao [15]: Output-stationary dataflow

They are diverse and chosen to support various existing as well emerging workloads. Table 4 presents MOHaM configuration for the experiments, where the GA exploration parameters are based on the guidelines of the widely adopted [16] and architectural parameters are based on the state-of-the-art.

3) Solution Anatomy: Figure 6 presents the scheduling Gantt chart and the area breakdown of SA for two Pareto-optimal solutions found by MOHaM for the AR/VR workload. The Gantt chart shows on the y-axis, the instantiated SAS (SAIs), and on the x-axis, the start and end times of the execution of each DNN layer, measured in cycles. Each bar represents the execution of a layer of the AM(L, D) on a particular SAI. Layers from different DNN models are depicted with different opacity, while layers executed on instances of different SATs are depicted with different colours. Segments with black traces represent bandwidth-constrained execution segments as described in Section V-C1. The pie chart on the right displays the area contribution of each SAI with different opacity, namely the MAS area breakdown. Instances from the same SAT have the same colour. It can be noticed that the two solutions shown here are very different in terms of their scheduling and sub-accelerator instantiation preferences.

B. Results

For all the 3D plots shown in Figures 7, 8 and 9, the more left and top a solution lies, the better it is in performance. For the ease of readability, the plots report the projection of the solution points on three different planes, i.e., latency, energy and area. A common observation valid for all the results presented in this section is the distribution of the solutions found by the proposed MOHaM framework. In fact, they are spread over a large Pareto surface rather than being limited to a specific region. This is an important advantage of MOHaM as it provides a variety of trade-off solutions from which the most appropriate for the specific use case can be selected.

1) Independent vs Simultaneous Optimisation: This experiment evaluates the need for hardware-mapping co-optimisation in multi-accelerator systems. Figure 7 shows the comparison of Pareto-optimal solutions with hardware-only, mapping-only and hardware-mapping co-optimisation. For hardware-only optimisation, the proposed MOHaM framework is run with only Simba-like SA templates to have a fixed dataflow (e.g., weight-stationary), similar to ConfuciuX [26]. For mapping-only optimisation, MOHaM is run with a fixed hardware configuration of 16 heterogeneous SAs, similar to MAGMA [28]. Finally, they are compared with the result of a complete MOHaM run for hardware-mapping co-optimisation. It is observed that for the AR/VR workload, hardware-only optimisation (red) has lower energy and area but high latency. This is due to the fixed mapping (dataflow) strategy for all the layers. Whereas mapping-only optimisation (blue) has lower latency
Figure 6: Comparison of scheduling Gantt chart and SA area contribution for two Pareto-optimal solutions.

Figure 7: Comparison of Pareto-optimal solutions with hardware-only, mapping-only, and hardware-mapping co-optimisation.

Figure 8: Comparison of Pareto-optimal solutions with homogenous and heterogenous sub-accelerators.

Figure 9: Comparison of individual solutions with mono-objective and Pareto-optimal solutions with multi-objective exploration.
and energy but at the cost of a very high area. This is due to the fixed hardware configuration. In general, across all the workload scenarios, hardware-only optimisation has better energy and area but poor latency. Similarly, mapping-only optimisation has better latency and energy but high area. With hardware-mapping co-optimisation, the solutions (black) are very interesting. For example, for the Data Center workload, they have solutions with lower latency and energy along with minimum area. They have equally competitive solutions across other workloads. This is a result of the proposed MOHaM framework instantiating the SAs with optimal hardware resources and mapping the layers according to their dataflow preferences for optimal execution. Hardware-mapping co-optimisation can accommodate diverse workloads and offer the best overall performance in a multi-accelerator system.

2) Homogeneous vs Heterogeneous Accelerators: This experiment evaluates the need for heterogeneous SAs in multi-accelerator systems. Figure 8 shows the comparison of Pareto-optimal solutions with homogeneous and heterogeneous SAs. For homogeneous SAs, the proposed MOHaM framework is run once, each with only Eyeriss-like, Simba-like, and ShiDianNao-like SA templates. Then, they are compared with the result of a complete MOHaM run for heterogeneous SAs. It is observed that for the Mobile workload, Eyeriss (blue) has lower latency and area but at the cost of high energy. On the contrary, ShiDianNao (red) is both energy and area efficient but at the cost of very high latency. For the Edge workload, Simba (yellow) has the best while ShiDianNao has the worst latency, respectively. Eyeriss has lower latency, energy as well as area. In general, among the solutions with homogeneous SAs, Simba has better latency while ShiDianNao has a better area. With heterogeneous SAs, the solutions (black) are more uniformly distributed. For example, for the AR/VR workload, they have solutions with the lowest latency, lowest energy and lowest area. Their solutions are equally good for the Data Center and other workloads. It is possible as layers with specific dataflow preferences can be executed on the appropriate SAs. The proposed MOHaM framework instantiates the right set of SAs from the available templates and maps the layers for efficient execution. Hence, flexible dataflow with heterogeneous SAs increases the scalability of a multi-accelerator system toward diverse and emerging workloads.

3) Single-Objective vs Multi-Objective Exploration: This experiment evaluates the need for multi-objective exploration in multi-accelerator systems. Figure 9 shows the comparison of individual solutions with mono-objective and Pareto-optimal solutions with multi-objective exploration. For mono-objective exploration, the proposed MOHaM framework is run once, each with only latency, and energy as an objective. Then, they are compared with the result of a complete MOHaM run for multi-objective exploration. When objectives conflict, improving one results in worsening the other. For example, for the Data Center workload, the solution with energy as an objective (blue) is at the extreme left (i.e., best), but the latency and area are worst. Similarly, the solution with latency as an objective (red) is best while the area is worst. A multi-accelerator system design is usually explored with more than one objective. Existing works aggregate them into a single solution (e.g., EDP), which suffers if they conflict. Other commonly used forms of aggregations, like the weighted sum of cost functions, do not allow to explore the non-convex regions of the design space. MOHaM supports distinct multi-objective exploration and provides a Pareto-optimal set of solutions (black). For the same Data Center workload, it provides multiple competitive solutions with the lowest energy, latency and area. Similar solutions are available across all the workloads. Multi-objective exploration helps identify the most suitable design for a multi-accelerator system as per the need.

4) Comparison with state-of-the-art: This experiment evaluates MOHaM against two popular state-of-the-art frameworks, CoSA [24] and GAMMA [27]. Like MOHaM, these frameworks also extended Timeloop [39] and are open-sourced, hence considered for a fair comparison. Please note that the simulations for CoSA and GAMMA are conducted using appropriate architectures with flexible dataflows without considering the reconfiguration overheads. Figure 10 shows a subset of Pareto-optimal design points obtained by MOHaM along with the design points by CoSA and GAMMA for the AR/VR workload. MOHaM clearly shows the ability to generate better design points than its competitors. For example, the design point ▲ improves latency by 16.5% and energy by 3.6% compared to CoSA, and latency by 7.1% and energy by 4.7% compared to GAMMA. Based on the specific requirements, other design points can also be considered. For example, if energy is the priority, design point ▼ improves energy by 21.2% and 22% compared to CoSA and GAMMA, at the cost of 17.3% and 29% decrease in latency, respectively.

5) Sensitivity of NoP Link Bandwidth: MOHaM calculates latency by combining and processing results of individual Timeloop [39] simulations and considering an NoP for data transfer between MIs to SAI. Hence, latency depends on the NoP hosting tile of each SAI, the amount of data accessed from memory, determined by the layer mappings, and the NoP link bandwidth. Figure 11 shows the latency of Pareto-optimal design points by MOHaM with varying NoP link bandwidth for the AR/VR workload. Apart from some exceptions due to the stochastic nature of GAs, there is a trend of decreasing latency but at the cost of a very high area.
6) Ablation Study: This experiment evaluates the effectiveness of the custom genetic operators implemented for the MOHaM framework. It compares the results of a complete MOHaM run with the results of runs, each with one operator disabled (ablated). Figure 9 shows the percentage of Pareto-dominated solutions when an operator is ablated from the baseline MOHaM configuration. Figure 12: Percentage of Pareto-dominated solutions when an operator is ablated from the baseline MOHaM configuration. The percentage increases with increasing bandwidth. However, bandwidth beyond 16 GB/s does not seem to improve the latency significantly.

VIII. DISCUSSION

MOHaM is used offline at design time to obtain a Pareto-optimal set of $MAS$ and an optimal $S$ for each of them. Hence its search time is irrelevant to the performance of the chosen $MAS$ and $S$. When the $MAS$ is deployed, it is assumed to employ batch processing, which is very common in data centers. A batch may have DNN models from heterogeneous application domains. Based on their specific requirements, $S$ schedules these models on the heterogenous $SA$s of the $MAS$. What might seem just like multi-workload scheduling is also multi-tenant, as heterogeneous DNN models execute in parallel. MOHaM uses $SA$s with fixed dataflow as state-of-the-art Herald [33] found them better over $SA$s with flexible dataflow. Nevertheless, MOHaM is can deal with flexible dataflow and full mapping search. Any $SA$ that Timeloop [39] supports can be given as an input to MOHaM.

IX. CONCLUSION

This work presents MOHaM, a multi-objective hardware-mapping co-optimisation framework for multi-tenant DNN accelerators. The key takeaways are: (1) The ever-increasing computation demand led to the design of multi-accelerator systems, where hardware-mapping co-optimisation is very important. However, due to the enormous cross-coupled search space, very few works explored the design space (refer Table 1). (2) Multi-tenancy is a primary enabler of scalability.
in multi-accelerator systems. However, most of the existing works employ manually-designed supports that limit accelerator utilization and deployment benefits. (3) Multi-accelerator systems are often designed for multiple objectives, yet no work exists for multi-objective exploration. (4) MOHaM is the first open-source framework to consider all these limitations. (5) MOHaM also has infrastructure for NoP/data movement.

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