A Two-Sided Matching Model for Data Stream Processing in the Cloud – Fog Continuum

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Abstract—Latency-sensitive and bandwidth-intensive stream processing applications are dominant traffic generators over the Internet network. A stream consists of a continuous sequence of data elements, which require processing in nearly real-time. To improve communication latency and reduce the network congestion, Fog computing complements the Cloud services by moving the computation towards the edge of the network. Unfortunately, the heterogeneity of the new Cloud – Fog continuum raises important challenges related to deploying and executing data stream applications. We explore in this work a two-sided stable matching model called Cloud – Fog to data stream application matching (CODA) for deploying a distributed application represented as a workflow of stream processing microservices on heterogeneous computing continuum resources. In CODA, the application microservices rank the continuum resources based on their microservice stream processing time, while resources rank the stream processing microservices based on their residual bandwidth. A stable many-to-one matching algorithm assigns microservices to resources based on their mutual preferences, aiming to optimize the complete stream processing time on the application side, and the total streaming traffic on the resource side. We evaluate CODA through simulations and real-world Cloud – Fog experimental scenarios. We achieved 11–45% lower stream processing time and 1.3–20% lower streaming traffic compared to related state-of-the-art approaches.

Index Terms—Cloud – Fog computing, computing continuum, matching game algorithm, microservice, data stream processing.

I. INTRODUCTION

The world is witnessing an exponential growth in the amount of generated data in the presence of pervasive Internet connectivity. Latency-sensitive and bandwidth-intensive data stream processing services, such as live video and video-on-demand streams, are amongst the dominating high-velocity traffic generators in today’s world. Processing such data streams in nearly real-time requires vast amounts of computational and network resources in proximity of the data sources. However, the high communication penalty for reaching the Cloud data centers significantly hinders the timely processing of the data streams. Fog computing complements the Cloud services by moving the computation towards the edge of network. The extension of the Cloud with distributed micro-data centers (also called cloudslets) and mobile Edge servers forms the so-called Cloud – Fog continuum, which aids the application execution by improving the communication latency and reducing the network congestion.

However, the heterogeneity of the Cloud – Fog continuum raises multiple challenges for executing data stream processing applications, including application deployment and resources allocation. Unfortunately, existing works often omit to consider data stream applications with strict latency and bandwidth requirements. It becomes therefore essential to explore models for allocating resources to data stream processing applications in the Cloud – Fog continuum.

We propose a two-sided matching model called Cloud – Fog to Data stream application matching (CODA) to address the problem of deploying data stream processing applications organized as directed acyclic graphs on heterogeneous computing continuum resources. CODA addresses this problem using matching theory principles involving two sets of players:

- Application microservices rank the continuum resources based on their microservice stream processing time (also referred to as microservice time);
- Cloud – Fog resources rank the stream processing microservices based on their residual bandwidth.

The CODA two-sided stable matching model assigns microservices to resources based on their mutual preferences, aiming to optimize the stream processing time on the application side, and the total streaming traffic on the resource side.

Hence, the main contributions in this work are:

- A model for quantifying the microservice stream processing time and the residual network bandwidth to a resource;
- A ranking strategy tailored to data stream applications that avoids zero bandwidth surplus;
- A many-to-one matching model that allocates resources based on their capacity to multiple microservices;
- A two-sided stable matching model for allocating Cloud – Fog resources to a microservice-based data stream processing application.

The paper has eight sections. Section II surveys the relevant related work. Section III elaborates the model underneath our approach, followed by the CODA matching algorithm in Section IV. Section V describes the stream processing case study application, evaluated using simulation in Section VI. Section VII confirms the simulation in a real-world testbed and Section VIII concludes the paper.
II. RELATED WORK

This section reviews the state-of-the-art in Cloud – Fog resource allocation for data stream processing applications with reduced network streaming traffic.

a) Hierarchical resource allocation: Gupta et al. [8] proposed a hierarchical placement strategy that executes the last microservice of every application in the Cloud and places all its predecessors on the less powerful computational resources in the Cloud – Fog hierarchy. Similarly, Mortazavi et al. [2] presented a novel paradigm called CloudPath computing that enables data stream processing on a progression of Cloud data centers based on their computing and storage capabilities, interposed along the geographical span of the network.

b) Stream processing time reduction: Sharghivand et al. [9] proposed a two-sided matching model for allocating Fog resources to services at the edge of network considering the service response time. The approach improves the user satisfaction and quality of experience using a set of heterogeneous quality of service metrics. Cai et al. [10] also addressed the service response time by defining a placement optimization model for complex event-processing applications on Edge resources. The proposed approximation algorithm deploys the operators on the Edge infrastructure with the lowest predicted delay. Veith et al. [11] proposed a placement strategy called RTR-RP, which uses a greedy strategy to identify the resources that minimize the service response time by reducing the end-to-end event latency of a data stream analytic application. This approach decomposes the application in data processing flow patterns such as fork and join, and then distributes it on the Cloud – Fog continuum. Dautov et al. [12] describes a new approach for stream data processing in Fog by supporting run-time clustering of heterogeneous low powered devices. Besides, they utilise horizontal offloading of computational tasks between the Fog devices, which results in reduction of the communication latency by a factor of five compared to the vertical offloading approaches that rely on the Cloud.

c) Streaming traffic reduction: Aral et al. [3] considered the Fog computing characteristics to improve the user experience for latency-sensitive applications. The service placement evaluates the network quality of each Cloud and Fog node with respect to its requirements, in particular the connectivity and bandwidth. Zamani et al. [13] describe a semi-real time data stream processing approach at the edge of the network, which supports stream transformation and analysis from source to destination. The approach leverages an in-network computational model that employs software defined networks to dynamically establish data stream routes that exploit the underutilized computational resources at the Edge.

d) CODA contribution: These works investigate the resource allocation as an optimization problem that minimizes the stream processing time as a main objective, and neglect the streaming traffic. We extend the related approaches by researching a novel resource provisioning approach based on two-sided matching [12] that considers different interests of the involved stakeholders:

1) minimization of the stream processing time from the application perspective;
2) minimization of traffic considering changes in the data stream rate from the resource provider perspective.

III. MODEL

This section presents a formal model and a set of essential definitions important for this work.

A. Stream application

We model a data stream processing application:

\[ \mathcal{A} = (\mathcal{M}, \mathcal{E}, m_{src}, m_{snk}, src, snk) \]

as a directed acyclic graph (DAG) consisting of:

1) A set of \( N_{\mathcal{M}} \) lightweight interconnected microservices:

\[
\mathcal{M} = \{ m_i \mid 0 \leq i < N_{\mathcal{M}} \};
\]

2) A set of data streams \( data_{ui} \) flowing from an upstream microservice \( m_i \) to a downstream microservice \( m_i \in \mathcal{M} \):

\[
\mathcal{E} = \{ (m_u, m_i, data_{ui}) \mid (m_u, m_i) \in \mathcal{M} \times \mathcal{M} \};
\]

3) A source microservice \( m_{src} \) processing the data stream produced by \( src \) of the application \( \mathcal{A} \). The source microservice has no upstream microservices:

\[
(m_{src}, m_i, src) \in \mathcal{E} \land \nexists (m_i, m_{src}, \_ \_ ) \in \mathcal{E};
\]

4) A sink microservice \( m_{snk} \) generating the data stream for \( snk \), representing the output of the application \( \mathcal{A} \).

\[
(m_i, m_{snk}, snk) \in \mathcal{E} \land \nexists (m_{snk}, m_i, \_ \_ ) \in \mathcal{E}.
\]

We define a data stream using the following triple notation:

\[ data_{ui} = (data_{ui}[x], \lambda_{ui}, \text{Size}_{ui}) \], where:

1) \( data_{ui} \) represents a sequence of data stream elements sent between two microservices \( m_u \) and \( m_i \), measured in bit;
2) \( data_{ui}[x] \) is a single data element in the data stream \( data_{ui} \).

We assume that \( m_i \) recognizes the data elements in the stream \( data_{ui} \) by the timestamp and merges the elements in the correct order;

3) \( \lambda_{ui} \) represents the ingress data rate that the microservice \( m_i \) receives a number of data elements per unit of time from its upstream microservice \( m_u \) [15].

4) \( \text{Size}_{ui} \) is the total number of data elements \( data_{ui}[x] \) transmitted in a stream \( data_{ui} \), where \( 1 \leq x \leq \text{Size}_{ui} \).

 Proper processing of a data element \( data_{ui}[x] \) by a microservice \( m_i \) has certain resource requirements in terms of the processing load CPU (\( m_i, data_{ui}[x] \)) (measured in million of instructions (MI)), memory MEM (\( m_i, data_{ui}[x] \)) and storage STOR (\( m_i, data_{ui}[x] \)) (measured in MB).
B. Resource model

We define a Cloud – Fog environment as a set of $\mathcal{N}_R$ resources: $\mathcal{R} = \{ r_j | 0 \leq j < \mathcal{N}_R \}$, where a resource $r_j$ defines its computational power $CPU_j$ (in MI per second), memory size $MEM_j$, and storage size $STOR_j$; $r_j = (CPU_j, MEM_j, STOR_j, c_j)$. We define the capacity $c_j$ of a resource $r_j$ as the maximum number of microservices it can host, which relies on its utilization as a threshold [16], [17] that ensures no contention among the microservices [18].

We model the network channels between the Cloud – Fog resources as $\mathcal{L} = \{ l_{qj} | 0 \leq q, j < \mathcal{N}_R \}$, where $l_{qj} = (LAT_{qj}, BW_{qj})$ represents the round-trip latency $LAT_{qj}$ and network bandwidth $BW_{qj}$ between the resources $r_q$ and $r_j$. Two interdependent microservices allocated to the same resource have $LAT_{qj} = 0$ and $BW_{qj} = \infty$ [19].

We define a microservice allocation as a mapping function $\mu : \mathcal{A} \to \mathcal{R}$ that assigns a microservice $m_i$ to a resource $r_j = \mu(m_i)$. Accordingly, $\text{alloc}(r_j)$ represents the list of microservices allocated and deployed on each resource $r_j$:

$$\text{alloc}(r_j) = \{ m_i | \mu(m_i) = r_j \}.$$  

C. Ranking methods

The CODA model for matching application microservices to resources uses a two-sided ranking method:

- microservice-side ranking that considers the stream processing time of each microservice;
- resource-side ranking that considers the residual bandwidth to each resource allocated to each microservice.

1) Microservice-side ranking: We define the element processing time $t(m_i, data_{ui}[x], r_j)$ required by a microservice $m_i$ to process the $x^{th}$ element $data_{ui}[x]$ of a stream received by a resource $r_j = \mu(m_i)$ as the sum of three terms:

$$t(m_i, data_{ui}[x], r_j) = \frac{CPU(m_i, data_{ui}[x])}{CPU_j} + \frac{data_{ui}[x]}{BW_{qj}} + LAT_{qj},$$

(a) computation time: as the ratio between the computational requirement $CPU(m_i, data_{ui}[x])$ for processing a data element $data_{ui}[x]$ on the microservice $m_i$ and the processing speed $CPU_j$ of the resource $r_j$;

(b) transmission time: as the ratio between the size of the received data element $data_{ui}[x]$ and the network bandwidth $BW_{qj}$ to $r_j = \mu(m_i)$ [20];

(c) latency: as the round-trip time $LAT_{qj}$ between resources $r_q$ and $r_j$.

The microservice stream processing time $T(m_i, data_{ui}[x], r_j)$ of a data stream $data_{ui}$ processed by a microservice $m_i$ running on a resource $r_j$ is the sum of its element processing times $t(m_i, data_{ui}[x], r_j)$:

$$T(m_i, data_{ui}[x], r_j) = \sum_{x=1}^{\text{Size}_{ui}} t(m_i, data_{ui}[x], r_j).$$

Every microservice $m_i$ ranks the resources in a resource preference list $\text{RPL}[m_i]$ based on the microservice stream processing time, as presented in Algorithm 1. The resource that guarantees a lower microservice time receives a higher rank. The algorithm first initializes the resource preference lists for each microservice with the empty set in line 1. Thereafter, it filters the resources that do not satisfy the memory $MEM(m_i, data_{ui}[x])$ and storage $STOR(m_i, data_{ui}[x])$ requirements of a microservice (line 5). Afterward, it creates a list of tuples for each microservice $m_i$ that associates the maximum microservice time $T(m_i, data_{ui}[x])$ of all upstream microservices $m_u$ of $m_i$ to each resource $r_j$ (line 7). Finally, the algorithm sorts the resource preferences of each microservice based on its microservice time in descending order in line 12.

2) Resource-side ranking: We model the residual bandwidth to a resource $r_j$ as the difference between the available bandwidth $BW_{qj}$ and the ingress traffic from an upstream microservice, as defined in the DAG structure of the applications. The ingress traffic is the amount of data per time unit received by a resource $r_j$ allocated to a microservice $m_i$, which depends on ingress data rate $\lambda_{ui}$ and data stream $data_{ui}$:

$$\text{ResdBW}(m_i, data_{ui}[x], r_j) = BW_{qj} - \sum_{x=1}^{\text{Size}_{ui}} (\lambda_{ui} \cdot data_{ui}[x]).$$

The resource-side ranking, presented in Algorithm 2, receives as input the resource preference lists $\text{RPL}[m_i] \ (\forall m_i \in \mathcal{A})$ computed in Algorithm 1 along with the application $A$, the resource set $\mathcal{R}$, and the set of network channels $\mathcal{L}$. Similarly, the algorithm initializes the microservice preference list $\text{NPL}[r_j]$ of each resource with the empty set in line 1. Afterward, each resource ranks the microservices in a preference list in line 6 based on its residual bandwidth. Finally, the algorithm sorts the microservice preferences in descending order in line 10 based on the residual bandwidth. Hence, the microservice that offers a lower bandwidth utilization receives a higher rank.

D. Problem definition

Matching theory is a formal framework describing the interactions among interdependent rational entities and forming mutually beneficial relationships over time [21]. The analytical matching theory helps to assign a set of rational entities to one
Algorithm 2 Resource-side ranking algorithm.

Input: \( A = (\mathcal{M}, \mathcal{E}, m_{\text{src}}, m_{\text{snk}}, \text{src}, \text{snk}) \) \( \triangleright \) Stream application.
\( R = \{ r_{j} \mid 0 \leq j < N_{R} \} \) \( \triangleright \) Cloud – Fog resource set.
\( \text{RPL}[m_{i}, \forall m_{i} \in \mathcal{M}] \) \( \triangleright \) Resource preference list of all microservices \( m_{i} \).
\( \mathcal{L} = \{ l_{ij} \mid 0 \leq j < N_{\mathcal{L}} \} \) \( \triangleright \) Cloud – Fog channel set.

Output: \( \text{MPL}[r_{j}, \forall r_{j} \in R] \) \( \triangleright \) Microservice preference lists of all resources \( r_{j} \).

1: for all \( r_{j} \in R \) do \( \triangleright \) Initialize MPL
2: MPL[\( r_{j} \)] \( \rightarrow \) 0
3: end for
4: for all \( m_{i} \in \mathcal{M} \) do
5: for all \( (r_{j} \in \text{RPL}[m_{i}]) \land (l_{ij} \in \mathcal{L}) \) do
6: MPL[\( r_{j} \)] \( \rightarrow \) MPL[\( r_{j} \)] \( \cup \) (\( m_{i} \), \( \text{Read}\text{BW}_{ij} \))
7: end for
8: end for
9: for all \( (r_{j} \in R) \land (\text{MPL}[r_{j}] \neq \emptyset) \) do
10: MPL[\( r_{j} \)] \( \rightarrow \) \text{Sort}_{\text{BW}}(\text{MPL}[r_{j}]) \( \triangleright \) Sort tuples based on residual bandwidth
11: end for
12: return MPL.

IV. CODA MATCHING ALGORITHM

Algorithm 3 describes the many-to-one matching-based allocation of microservices to resources. The algorithm receives as input the stream application described as a DAG, the resource preference list RPL of each microservice \( m_{i} \), and the microservice preference list MPL of each resource \( r_{j} \), computed by Algorithms 1 and 2. The algorithm outputs a stable matching between microservices and resources \( \mu(A) \subseteq R \) . After initializing the allocation on both sides (lines 10–16), the algorithm loops until it manages to find the appropriate resource allocation matches to all microservices according to their mutual preferences (lines 18–45). In every iteration, it attempts to find a good resource matching for every microservice using several matching states (i.e. State-1, State-2.1, State-2.2), described in the following paragraphs.

1) State-1: Each microservice not yet matched to any resource demands the resource \( r_{j} \) with the lowest microservice time, ranked first in its preference list RPL[\( m_{i} \)] (lines 18–10). If the resource \( r_{j} \) has also ranked the microservice first in its preference list MPL[\( r_{j} \)] because of the least bandwidth consumption (line 11), the algorithm creates a matching pair and update the resource \( \mu(m_{i}) \) and the list of microservices alloc(\( r_{j} \)) (lines 12–13).

2) State-2: If the microservice \( m_{i} \) is not the first in the preference list MPL[\( r_{j} \)] (line 15), \( m_{i} \) matches to \( r_{j} \) (lines 16–17). Afterward, the algorithm checks the following two states:

   a) State-2.1: If \( m_{i} \)'s allocation to resource \( r_{j} \) exceeds its capacity \( c_{j} \) (line 18), the algorithm removes the allocation \( \mu(m_{i}) = r_{j} \) with the lowest residual bandwidth in the ranked preference list MPL[\( r_{j} \)] of resource \( r_{j} \) (lines 19–21).

   b) State-2.2: If a resource \( r_{j} \) reaches its capacity \( c_{j} \) (line 24), the algorithm identifies the microservice \( m_{u} \) with the lowest residual bandwidth in its allocation list alloc(\( r_{j} \)) (line 25). Afterward, \( r_{j} \) removes all microservices \( m_{s} \) with a lower residual bandwidth than \( m_{u} \) from its preference list MPL[\( r_{j} \)]. Similarly, all microservices \( m_{s} \) remove \( r_{j} \) from their resource preference lists RPL[\( m_{s} \)]. This avoids deploying microservices with low residual bandwidth on \( r_{j} \) and allows higher ranked microservices in MPL[\( r_{j} \)] to fill its capacity (lines 26–28).

3) CODA complexity: The microservice-side ranking (Algorithm 1) and the resource-side ranking (Algorithm 2) algorithms have complexity of \( O(N_{M} \cdot N_{R}) \), where \( N_{M} \) is the number of microservices and \( N_{R} \) is the number of resources allocated to the microservices. Algorithm 3 traverses the microservice \( m_{i} \)'s resource preference list RPL[\( m_{i} \)] that previously ranked all the resources (outputs of Algorithms 1 and 2). Therefore, its worst-case time complexity directly depends on the number of acceptable matches, which is \( N_{M} \cdot N_{R} \). The complexity of the sorting algorithm Sort_{\text{BW}} must consider the maximum capacity of the resources \( c_{\text{max}} = \max(c_{j}) : \forall j \leq N_{R} \). Considering the use of a quick-sort algorithm, this leads to a total runtime complexity of Algorithm 3 of \( O(c_{\text{max}} \cdot \log(c_{\text{max}}) \cdot N_{M} \cdot N_{R}) \).

4) CODA trace example: Figure 4 illustrates an example of using Algorithm 3 on five microservices and four resources.

Another, typically subject to constraints such as preference lists and capacities [22].

We represent our resource allocation problem as a matching game using two finite and disjoint sets of players: 1) the microservices \( \mathcal{M} \) of the stream processing application \( A \), and 2) the Cloud – Fog resources in \( R \). The game aims to match each microservice \( m_{i} \in \mathcal{M} \) to a resource in \( r_{j} \in R \) with sufficient capacity that optimizes two independent goals: 1) application-specific on one side and 2) resource provider-specific on the other side. The result is a bilateral resource allocation agreement that represents the players’ preferences over each other. Section VI-C instantiates this problem on two metrics: 1) stream processing time on the application side, and 2) total streaming traffic on the resource side.

In a matching game, a microservice \( m_{i} \in \mathcal{M} \) asks for allocation on the first resource \( r_{j} \) in its preference list RPL[\( m_{i} \)]. If \( r_{j} \) has enough capacity \( c_{j} \) and there exists no other preferred microservice in its preference list MPL[\( r_{j} \)], it bids for \( m_{i} \). If the two sides agree, the microservice \( m_{i} \) holds its demand from the resource \( r_{j} \) and vice versa until the matching completes.

A valid resource allocation is (pairwise) stable if it satisfies three properties of a many-to-one matching game [23, 24]:

1) Each microservice is allocated to exactly one resource from its preference list:

\[ \mu(m_{i}) \in R \land |\mu(m_{i})| = 1 \lor \mu(m_{i}) \in \text{RPL}[m_{i}]; \]

2) A resource can host multiple microservices that are part of its preference list and within its capacity:

\[ \text{alloc}(r_{j}) \subseteq \text{MPL}[r_{j}] \subseteq \mathcal{M} \land |\text{alloc}(r_{j})| \leq c_{j}; \]

3) The matching does not contain blocking pairs of microservices and resources that prefer matching each other rather than their current assignments [17]. A matching \( r_{j} = \mu(m_{i}) \) is not blocking if the following conditions hold:

   a) \( m_{i} \) and \( r_{j} \) are currently matched with each other;
   b) \( m_{i} \) does not prefer another resource to its current matching \( r_{j} \);
   c) \( r_{j} \) does not prefer another microservice to any of its current matching in alloc(\( r_{j} \)).
Algorithm 3 CODA matching algorithm.

Input: $\mathcal{A} = (M, E, m_{src}, m_{snk}, src, snk)$  
\hspace{1em} $\triangleright$ Cloud – Fog resource set

$\mathcal{R} = \{r_j \mid 0 \leq j < N_R\}$  
\hspace{1em} $\triangleright$ Preference lists of all resources $r_j$

$\text{RPL}[m_i], \forall m_i \in M$  
\hspace{1em} $\triangleright$ Preference lists of all microservices $m_i$

Output: $R = s(\mathcal{A})$.

1: for all $m_i \in M$ do  
\hspace{1em} $\triangleright$ Initialize invalid microservice allocation
2: $\mu(m_i) \leftarrow \text{NaR}$  
\hspace{1em} $\triangleright$ Not a Resource
3: end for

4: for all $r_j \in R$ do  
\hspace{1em} $\triangleright$ Initialize empty resource allocation
5: alloc($r_j$) $\leftarrow$ $\emptyset$
6: end for

7: $\text{NaR}M \leftarrow M$  
\hspace{1em} $\triangleright$ Initialize list of Not-a-Resource microservices
8: while $\text{NaR}M \neq \emptyset$ do  
\hspace{1em} $\triangleright$ Allocate all microservices
9: $m_i \leftarrow \text{FIRST}(\text{NaR}M)$  
\hspace{1em} $\triangleright$ list of Not-a-Resource
10: $r_j \leftarrow \text{FIRST}(\text{RPL}[m_i])$  
11: if $m_i = \text{FIRST}(\text{RPL}[r_j]) \land |\text{alloc}(r_j)| \neq c_j$ then  
\hspace{1em} $\triangleright$ State-1
12: $\mu(m_i) \leftarrow r_j$  
\hspace{1em} $\triangleright$ Match $m_i$ and $r_j$
13: alloc($r_j$) $\leftarrow$ $\text{SORT}_\text{match}(\text{alloc}(r_j) \cup m_i)$
14: else  
15: if $m_i \in \text{MPL}[r_j] \land m_i \neq \text{FIRST}(\text{RPL}[r_j])$ then  
\hspace{1em} $\triangleright$ State-2
16: $\mu(m_i) \leftarrow r_j$  
\hspace{1em} $\triangleright$ Match $m_i$ and $r_j$
17: alloc($r_j$) $\leftarrow$ $\text{SORT}_\text{match}(\text{alloc}(r_j) \cup m_i)$
18: end if
19: if $\text{alloc}(r_j) > c_j$ then  
\hspace{1em} $\triangleright$ State-2.1
20: $m_u \leftarrow \text{LAST}(\text{alloc}(r_j))$
21: $\mu(m_u) \leftarrow \text{NaR}$  
\hspace{1em} $\triangleright$ Reject $m_u$ from $r_j$
22: alloc($r_j$) $\leftarrow$ $\text{alloc}(r_j) \setminus m_u$
23: $\text{NaR}M.\text{APPEND}(m_u)$  
\hspace{1em} $\triangleright$ Add $m_u$ to list of Not-a-Resource
24: end if
25: if $|\text{alloc}(r_j)| = c_j$ then  
\hspace{1em} $\triangleright$ State-2.2
26: $m_u \leftarrow \text{LAST}(\text{alloc}(r_j))$
27: for all $m_i \in \text{MPL}[r_j] \land \text{RANK}(m_u) \leq \text{RANK}(m_i)$ do  
\hspace{1em} $\triangleright$ State-2.2.1
28: $\text{RPL}[m_i] \leftarrow \text{RPL}[m_i] \setminus r_j$
29: if $\text{RPL}[m_i] = \emptyset$ then  
\hspace{1em} $\triangleright$ State-2.2.2
30: $\text{NaR}M.\text{REMOVE}(m_i)$  
\hspace{1em} $\triangleright$ Remove $m_i$ if it has no pref
31: end if
32: end for
33: end if
34: end if
35: end if
36: end while

This converges to a stable matching. Each resource has the capacity to allocate at most two microservices. We assume that Algorithms 1 and 2 already created the microservice and resource preference lists (displayed in brackets in Figure 1). Figure 1a shows the matching of the microservice $m_1$ to the resource $r_1$ (lines 16-17). Figure 1a also depicts the matching of $m_2$ to $r_4$ (ranked highest in each other preference lists) following the State-1 of the algorithm (lines 12-13). Afterward, $m_3$ matches to $r_1$, as shown in Figure 1b (lines 12-13). In addition, Figure 1c illustrates that the microservices with lower residual bandwidth in the resources preference lists (i.e., not ranked first) demand resources, and thus, $m_4$ matches to $r_4$ (lines 16-17). As a consequence, $r_1$ reaches its total capacity and removes the lower-ranked microservices $m_5$ and $m_4$ (with a lower residual bandwidth than $m_1$) from its preference list (State-2.2). The microservices $m_5$ and $m_4$ also remove $r_1$ from their preference lists (lines 25-28). In the next outer loop iteration (line 8), the remaining microservice $m_5$ demands its preferred resource $r_4$ (line 10). Therefore, $r_4$ and $m_5$ match one another (lines 16-17), although $r_4$ already reached its total capacity. This matching is not successful, as the capacity of $r_4$ is full (State-2.1). However, $m_5$ has a higher rank than $m_4$ due to its higher residual bandwidth; therefore, the matching of $m_4$ to $r_4$ fails (lines 19-21). As a consequence, $r_4$ removes $m_4$ (with lower residual bandwidth than $m_5$) from its preference list (State-2.2) and $m_4$ removes $r_4$ from its preference list too (State-2.2.1), as shown in Figure 1c. Finally, Figure 1d shows that the microservice $m_4$ matches resource $r_3$ (lines 16-17), as the only resource with enough capacity that prefers it.

V. CASE STUDY: VIDEO STREAM PROCESSING FOR TRAFFIC SIGN CLASSIFICATION

We selected a representative traffic management system case study following road safety inspection concerns. Detecting and recognizing different traffic signs and anomalies in nearly real-time requires fast detection of objects in video frames and embedding the information on the detected objects in video streams at different encoding resolutions and bit rates.

Typical examples are broken, covered, worn-out or stolen traffic signs, or incorrectly painted road surface markings.

We represent this application as a DAG of seven microservices depicted in Figure 2. Each independent microservice contains a data store and communicates with other microservices through a lightweight HTTP interface.

1) Encoding microservice: receives and encodes the raw video stream in high resolution and bitrate near to the vehicles
equipped with multiview-cameras. We use for this purpose the ffmpeg software suite [28] with the H.264 video codec for encoding, transcoding and packaging of the video streams.

2) Framing microservice: utilizes OpenCV to produce still frames from different video scenes [29].

3) Low-accuracy inference microservice: identifies features in the video stream, such as traffic signs on the road. The microservice uses TensorFlow core version 2.3.0 for Python v3.7.4 to train a convolutional neural network with nine layers on localized signs from 50,000 video frames of 43 different traffic sign classes. Every frame contains a traffic sign used for training and testing the neural network. This microservice aims for a low classification accuracy of 70%.

4) High-accuracy inference microservice: uses a machine learning model [30] capable of accurate inference when the low-accuracy microservice has a poor confidence. We use the same convolutional neural network with nine layers to classify the signs in the same video frames as for the low-accuracy inference until reaching a 90% accuracy.

5) Analysis microservice: updates and retrains the multiclass classification model to learn from newly collected data [31]. This microservice is the upstream of the high-accuracy inference and transcoding microservices and requires a barrier to synchronize the received data.

6) Transcoding microservice: converts the video in different resolutions and bitrates, and prepares it for delivery. We again use the ffmpeg software suite with the H.264 video codec for transcoding the video streams.

7) Packaging and delivery microservice: provides the transcoded video stream together with the detected signs in the format required by the drivers. This microservice is the downstream of analysis and transcoding microservices, and uses a barrier to synchronize the data received from its upstream microservices.

We used the Phoronix test suite [32] to benchmark the application microservices on a set of heterogeneous devices integrated in our testbed, described in Section VII. Afterward, we identified the requirements of the encoding, transcoding, packaging and inference microservices based on the average device utilization in terms of MI, memory, storage, dataui (in MB) and ingress data rate (in [s]). We summarize the video stream processing application requirements in Table 1.

|                | CPU [MIPS] | MEM [GB] | Storage [GB] | dataui [MB] | λui [/s] |
|----------------|------------|----------|--------------|-------------|----------|
| encoding       | 30 – 40    | 300 – 500| 1 – 5        | 0.1 – 10    | 0.2 – 40 |
| framing        | 1 – 5      | 100 – 300| 0.5 – 2      | 0.1 – 10    | 0.2 – 40 |
| low-accuracy inf | 5 – 20    | 200 – 300| 0.5 – 2      | 0.1 – 10    | 0.2 – 40 |
| high-accuracy inf | 30 – 40    | 300 – 500| 3 – 5        | 0.1 – 10    | 0.2 – 40 |
| analysis       | 10 – 20    | 100 – 300| 1 – 3        | 0.1 – 10    | 0.2 – 40 |
| transcoding    | 5 – 40     | 200 – 500| 0.5 – 5      | 0.1 – 10    | 0.2 – 40 |
| packaging      | 10 – 20    | 100 – 300| 1 – 2        | 0.1 – 10    | 0.2 – 40 |

VI. SIMULATION-BASED EVALUATION

We implemented the CODA matching-based resource allocation in Python v3.7.4 using the matching library [33]. The script required to run the CODA model is available in the GitHub code repository [1]. We utilize the iFogSim simulator [8] to perform the evaluation on a simulated Cloud – Fog environment.

A. Resource setup

Table 1 displays the simulated Cloud – Fog computing environment divided in three hierarchical tiers based on their computation, storage, and networking capabilities. We used the Phoronix test suite benchmark [32] to measure the performance of each resource and then use it in the simulation. The measured computational CPU power of the resources is in the range 20,000 MIPS – 100,000 MIPS.

1) Cloud data center: simulates instances equivalent to m5a.8xlarge of Amazon EC2, based on the 32-core AMD® EPYC 7571 processor with a clock frequency of 2.1 GHz. We select the m5a.8xlarge instance as it provides a good balance of computation, memory and network resources, suitable for executing data stream processing [34].

2) Fog-tier-2: simulates processing gateways (ISP GW) and cellular Base Transceiver Stations (BTS) available within Internet Service Providers (ISP) networks. We simulate the configuration based on the Alcatel-Lucent Ultimate Wireless Packet Core with 28-core Intel® Xeon Platinum 8175 and base clock frequency of 2.5 GHz [35].

3) Fog-tier-1: simulates resources co-located with the WiFi transceivers based on an eight-core Intel® Core(TM) i7-7700 CPU at 3.60 GHz equivalent configuration, widely used for data stream processing at the consumer premises [36].

4) Interconnection network: simulates various Ethernet, wireless LAN, and 4G/LTE interfaces. We assume that gigabit switches interconnect the Cloud data centers and the Fog resources. As the Cloud interconnection network multiplexes the streaming traffic of multiple instances, the throughput to the Cloud data center is lower than to the Fog resources because of the shared bandwidth. Hence, we chose a bandwidth BW in the range 200 Mbit s⁻¹ – 1000 Mbit s⁻¹ and a latency in

https://github.com/SiNa88/CODA.
TABLE II: Simulated Cloud – Fog infrastructure.

|                  | Cloud | Fog-tier-2 | Fog-tier-1 |
|------------------|-------|------------|------------|
| CPU [MIPS]       | 100   | {80,75}    | {20,30}    |
| Memory [GB]      | 128   | {64,32}    | {8,16}     |
| Storage [GB]     | 1200  | {250,128}  | {16,64}    |
| BW [Mbps]        | 200   | {200,500}  | {1000}     |

the range 3 ms – 100 ms for interconnecting the Cloud and Fog resources. We derived these values from the maximum achievable bandwidth and the effective downlink throughput measured using the iPerf3 tool [37], [38] (see Table II).

B. Experimental design

We designed two sets of experiments according to the characteristics of the video stream processing application.

1) CPU experiment: varies the requirement in the range of {10000, 20000, 30000, 40000} (MI) by bounding the data element to $data_{ui}[x] = 10$ MB, which is the largest data element supported by the simulated communication protocol.

2) Data experiment: varies the data element size $data_{ui}[x]$ transferred between microservices in the range {0.1, 1, 5, 10} MB, with a CPU requirement of 15000 MI.

C. Performance metrics

We compare the performance of our CODA method against related works based on two metrics.

1) Stream processing time: on the resources $\mu(A) \subseteq R$ is the completion time of the application $m_{snk}$ microservice:

$$C(A, R) = C(m_{snk}, R),$$

where the completion time of a microservice $m_i$ is the maximum completion time of all its upstream microservices $C(m_u, R)$ plus its microservice stream processing time $T(m_i, data_{ui}, r_j)$ on the allocated resource $r_j = \mu(m_i)$:

$$C(m_i, R) = \max_{\forall(m_u, m_i), \{C(m_u, R)\}} + T(m_i, data_{ui}, r_j), m_{src} = m_i, m_{snk} = m_i.$$

2) Total streaming traffic: aggregates the traffic across all network channels. We define the streaming traffic on a network channel $l_{qj}$ as the ratio of all the data elements $data_{ui}[x]$ streaming between the resources $r_q = \mu(m_u)$ and $r_j = \mu(m_i)$ allocated to two interdependent microservices and the bandwidth $Bw_{qj}$ of a channel between the two resources:

$$Str_{Traf}(A, R) = \sum_{\forall(m_u, m_i, data_{ui}[x]) \land l_{qj} \in L} \frac{\sum_{x=1}^{Size_{ui}} (\lambda_{ui} \cdot data_{ui}[x])}{Bw_{qj}}.$$

D. Related work comparison

We conducted the performance comparisons against three state-of-the-art approaches divided in two categories.

1) Cloud: uses only Cloud data centers for an application.

a) Heterogeneous Earliest Finish Time – only Cloud (HEFT-oC): deploys all microservices on the Cloud and selects the proper Cloud instances using a bottom ranking approach to optimize the stream processing time [39].

2) Cloud and Fog: uses a combination of Cloud data centers and Fog resources.

a) Response Time Rate with Region Patterns (RTR-RP): [11] minimizes the stream processing time by analyzing the data flow patterns to deploy the microservices on the Fog resources that offer the shortest stream processing time. The Cloud data center only hosts the microservices that do not fit on the Fog devices due to resource and network requirements.

b) CloudPath: [2] optimizes the stream processing time on a progression of Cloud data centers and Fog resources. CloudPath organizes the data centers in a multi-tier topology, and identifies first resources in the lowest tier (closest to the data src) that meet the application requirements. If such resources are not available, it checks in the upper layers until it finds appropriate allocation resource.

E. Simulation results

Figures 3 and 4 illustrate the relation between the stream processing time and the total streaming traffic by increasing the computation and communication loads.

1) CPU experiment:

a) Stream processing time: Figure 3a shows that CODA reduces the stream processing time by 22%, 12%, and 15% compared to RTR-RP, HEFT-oC and CloudPath. The related methods allocate Cloud resources to the last microservices residing farther away from the data src in the application DAG, which explains this result. RTR-RP allocates the Cloud resource to the snk microservice, which increases stream processing time, as the data needs to travel at least twice between the Cloud and the Fog-tier-1.

b) Total streaming traffic: Figure 3b shows that CODA reduces the average streaming traffic by 5%, 8% and 7% compared to RTR-RP, HEFT-oC and CloudPath by allocating resources in the Fog-tier-2 instead of Cloud virtual machines. As the data element size does not vary during the simulation, the streaming traffic does not change for microservices with different CPU requirements.

2) Data experiment:

a) Stream processing time: Figure 4a shows that CODA reduces the stream processing time by 89%, 9.7% and 11% compared to RTR-RP, HEFT-oC and CloudPath for different data element sizes. Unlike the other approaches, CODA considers the network bandwidth and the data element in its microservice-side ranking to find matches that reduce the streaming traffic, and consequently the processing time.

b) Total streaming traffic: Figure 4b shows that HEFT-oC and CloudPath generate higher streaming traffic than CODA and RTR-RP for small data elements. As the data element increases, the streaming traffic gradually saturates the network channels, and the related approaches perform almost equally well. CODA reduces the streaming traffic up to 23% compared to the related methods by considering the data element in its resource-side ranking.

VII. REAL TESTBED EVALUATION

To validate the simulation results, we analyze in this section the CODA performance on a real experimental testbed.
A. Carinthian Computing Continuum

We deployed a real testbed at the University of Klagenfurt named Carinthian Computing Continuum (C³) [40] that aggregates heterogeneous resources in three hierarchical categories [41], as depicted in Figure 3.

1) Cloud data center: consists of virtualized instances provisioned on-demand from the Amazon Web Services (AWS), located at the geographically closest European data center in Frankfurt (Germany). We selected the m5a.xlarge general purpose instance powered by AMD EPYC 7000 processors at 2.5 GHz and up to 10 Gbit s⁻¹ network bandwidth as the most suitable instance for our case study.

2) Fog-tier-2: comprises resources from two providers, Exoscale [42] and University of Klagenfurt, thanks to their low round-trip communication latency (≤ 7 ms) and high bandwidth (≤ 10 Gbit s⁻¹). University of Klagenfurt provides a private Cloud infrastructure (PCI) using OpenStack v13.0 and Ceph v12.2 with support for block and S3-compatible object storage. The computing optimized instances are of type large running Ubuntu 18.04 LTS, as described in Table III.

3) Fog-tier-1: comprises five NVIDIA Jetson Nano (NJN), three Raspberry Pi-3 B+ (RPi3B+), and 32 Raspberry Pi-4 single-board computers (RPi4). We installed Raspberry Pi OS (version 2020-05-27) on all RPi and Linux for Tegra (L4T) operating system on NJN resources. A managed layer-3 HP Aruba switch interconnects the Fog-tier-1 resources. The switch has 48 1 Gbit s⁻¹ ports, a latency of 3.8 µs and an aggregate data transfer rate of 104 Gbit s⁻¹. The Fog-tier-1 has a Fog/Edge Gateway System (EGS) as the entry point to the other resources available in this tier. The EGS has a twelve-core AMD Ryzen Threadripper 2920X processor at 3.5 GHz and 32 GB of RAM, running Ubuntu 18.04 LTS. It supports 1 Gbit s⁻¹ Ethernet and dual band PCIe WiFi 5 (802.11ac) network connections.

We installed a Docker engine 19.03 on all resources and containerized each microservice in Ubuntu 18.10 Docker official image. The minimal scripts to create and run the containerized microservices on the resources is available in the GitHub code repository [43].
### C. Real-world testbed results

1) **CPU experiments**: investigate the impact of CPU requirements for transcoding the raw video segment. We considered four encoding and transcoding bit rates of \{200, 1500, 3000, 6500, 20000\} kbits\(^{-1}\), corresponding to resolutions of \{180, 576, 720, 1440, 2160\} pixels. We further considered two machine learning models with 70% and 90% accuracy for the inference microservices with different CPU requirements. We fixed the size of the data element to 2560 kB.

2) **Data experiments**: compare the different methods using data element sizes in the range: \(data_{ui}[x] \in \{35, 300, 420, 1350, 2560\}\) kB, which correspond to different video frame sizes obtained by using five different qualities. We fixed the video resolution to 2160p.

#### B. Experimental design

We evaluated CODA compared to the related HEFT-oC, RTR-RP and CloudPath methods using the video stream processing application for traffic sign classification, described in Section V. We processed a raw video stream of 9s and 45 MB in size that includes the traffic signs. We designed two sets of experiments according to the application characteristics.

1) **CPU experiments**: investigate the impact of CPU requirements for transcoding the raw video segment. We considered four encoding and transcoding bit rates of \{200, 1500, 3000, 6500, 20000\} kbits\(^{-1}\), corresponding to resolutions of \{180, 576, 720, 1440, 2160\} pixels. We further considered two machine learning models with 70% and 90% accuracy for the inference microservices with different CPU requirements. We fixed the size of the data element to 2560 kB.

2) **Data experiments**: compare the different methods using data element sizes in the range: \(data_{ui}[x] \in \{35, 300, 420, 1350, 2560\}\) kB, which correspond to different video frame sizes obtained by using five different qualities. We fixed the video resolution to 2160p.

#### TABLE III: The C\(^3\) testbed configuration.

| Instance / Device | Cloud | Fog-tier-2 | Fog-tier-1 |
|-------------------|-------|------------|------------|
| AWS m5a.xlarge    | 300 Mbits\(^{-1}\) | 1 Gbits\(^{-1}\) | 1 Gbits\(^{-1}\) |
| CPU type          | AMD EPYC 7000 | AMD Ryzen 7 2600 | ARM Cortex A57 |
| Memory (GB)       | 256 | 32 | 2 |
| Storage (GB)      | 9600 | 256 | 32 |
| Bandwidth (MB/s)  | 1 Gbit/s | 1 Gbit/s | 1 Gbit/s |

#### Fig. 5: The C\(^3\) testbed architecture.
resources in the Fog-tier-2 layer with lower stream processing time. In contrast, CloudPath requires the data stream to traverse more network channels towards the data sink, which generates higher streaming traffic.

3) Conclusion: The real testbed evaluation confirms the simulation. Surprisingly, the benefits of CODA to the stream processing application are even higher compared to the three related methods due to the higher latency and lower bandwidth difference between the Fog-tier-1, Fog-tier-2 resources and the Cloud instances within the C³ testbed.

VIII. CONCLUSIONS AND FUTURE WORK

We introduced CODA, a novel approach for allocating heterogeneous Cloud – Fog computing resources to data stream processing applications, described as DAGs. CODA applies a two-sided stable matching model that enables many-to-one assignment of application microservices to resources based on specific ranking strategies. The microservices rank the continuum resources based on their microservice stream processing time. On the other side, resources rank the stream processing microservices based on their residual bandwidth. A two-sided stable matching model assigns microservices to resources based on their mutual preferences, aiming to optimize the complete stream processing time on the application side and the total streaming traffic on the resource side. We evaluated CODA based on a video stream processing application for traffic sign classification using comprehensive simulation combined with a real Cloud – Fog experimental testbed deployment. The results demonstrate that CODA achieves 11-45% lower stream processing times and 1.3-20% lower streaming traffic than three state-of-the-art approaches. In the future, we plan to further improve our results by analyzing Nash equilibrium while processing the data streams in the Cloud – Fog computing continuum.

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