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Abstract

Multi-edge cooperative computing that combines constrained resources of multiple edges into a powerful resource pool has the potential to deliver great benefits, such as a tremendous computing power, improved response time, more diversified services. However, the mass heterogeneous resources composition and lack of scheduling strategies make the modeling and cooperating of multi-edge computing system particularly complicated. This paper first proposes a system-level state evaluation model to shield the complex hardware configurations and redefine the different service capabilities at heterogeneous edges. Secondly, an integer linear programming model is designed to cater for optimally dispatching the distributed arriving requests. Finally, a learning-based lightweight real-time scheduler, CoRaiS, is proposed. CoRaiS embeds the real-time states of multi-edge system and requests information, and combines the embeddings with a policy network to schedule the requests, so that the response time of all requests can be minimized. Evaluation results verify that CoRaiS can make a high-quality scheduling decision in real time, and can be generalized to other multi-edge computing system, regardless of system scales. Characteristic validation also demonstrates that CoRaiS successfully learns to balance loads, perceive real-time state and recognize heterogeneity while scheduling.
CoRaiS: Lightweight Real-Time Scheduler for Multi-Edge Cooperative Computing

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Index Terms—Edge computing, Multi-edge cooperative computing, Deep learning, Real-time scheduling

I. INTRODUCTION

Edge computing brings computation and storage resources closer to the sources of data, facilitating the processing of client data at the network periphery while meeting stringent response time requirements. Some great progresses have been achieved, especially in the mobile edge computing [1], [2]. However, practical applications often reveal challenges. As shown in Fig. 1, each edge hosts a diverse set of services, and it typically serves multiple clients. The distribution of clients among edges exhibits non-uniformity, with variations in both the number of requests submitted by each client and the specific service they require. This complexity can potentially degrade service quality, especially when an edge is inundated with an excessive number of client requests.

The multi-edge cooperative computing combining constrained resources of multiple edges into a powerful resource pool can provide more diversified services and ensure sufficient computing and storage resources. Therefore, it has higher probability to meet the requirements by computation-intensive and latency-critical requests, and improve the average utilization of edges and response time of requests. The edge-cloud system can be regarded as a special case of multi-edge cooperative computing, because the cloud can be considered as an edge with significantly enhanced computational capabilities.

Many researchers are interested in the multi-edge cooperation system, and have proposed some algorithms [3]–[8] to schedule independent requests and requests with logical execution order in the system. They usually make some hypotheses to support their research. Firstly, only CPU is configured on the edges, and the number of calculations required to respond to each request is known. With such two conditions, the response time of each request can be obtained by dividing the calculation number by the CPU frequency. Secondly, the request arrival patterns follow known probability distributions, such as poisson distribution, multinomial distribution, etc. With such assumption, many statistical theories and models can be applied to the multi-edge scheduling problems.

However, the assumptions contradict many practical situations. (i) The heterogeneous edges are configured with various computing units, such as CPUs and GPUs. Especially, with increasing requests related to deep learning accessing to edges,
It has become a major trend to deploy GPUs at edges. (ii) It is difficult to estimate the calculation number required by requests. Because, when the corresponding processing code is black-box, the calculation number cannot be predicted in advance; when the code is white-box but includes some loop operation and judgment statements, the timing of jumping out of loops and the judgment results are also unpredictable, which makes the calculation numbers impossible to be estimated. (iii) The arrival pattern of requests is almost unpredictable. Each client has its own unique request generation pattern. Though the pattern of a single client can be estimated, it is difficult to analyze the composite pattern of multiple clients. Besides that, another two phenomenons should be focused on, i.e. during the execution process of a service, it will occupy multiple resources such as CPU, GPU, and Memory simultaneously, and the quality of service (QoS) varies across edges.

Based on the analysis above, we can identify that the multi-edge cooperative scheduling faces three challenges. (i) Multi-edge cooperative computing system state modeling: The diverse hardware composition and different resource allocation schemes for services at edges pose a severe problem for modeling system state. The QoS of edges would not be fairly evaluated, unless the edges heterogeneity can be shielded and an unified QoS evaluation method can be built. Meanwhile, the system state that includes remaining resource of CPU/GPU/Memory at edges keeps changing as the arrival, running, and completion of requests. Dispatching requests to edges based on the perfect initial state, like traditional approaches, will make the scheduling solution deviate from the optimal at the current state. Therefore, it is challenging but necessary to build a system-level state model that supports edges unified modeling and perceives dynamic changes of resource states. (ii) Multi-edge cooperative scheduling formulation: Most previous theoretical models were designed based on probability distribution assumption of requests and single computing hardware assumption of edges [9], [10], which may not accurately reflect real-world application scenarios. Some learning-based approaches [4], [5] are also studied to optimize the scheduling behaviours on some specific datasets and specially constructed multi-edge network. However, the generalization ability of the approaches is not good. Once the application and network environment change, a large amount of data (with expert knowledge sometimes) must be collected to retrain the scheduling model, while sometimes it is difficult to collect efficient data and expert knowledge. Therefore, a new mathematical formulation is required to reveal the essence of multi-edge cooperative scheduling problem and to guide scheduling algorithm research for requests with any arrival pattern. (iii) Real-time scheduler designing: The multi-edge scheduling problem for multiple requests is essentially a combinatorial optimization problem with some constraints. The search space of such problem is huge and will grow as the number of edges and requests increase. Computing an optimal solution in the huge search space is theoretically time-consuming. The previous works usually took a long time to make the scheduling decision. However, in practice, only methods that support real-time scheduling can ensure the efficient operation of the multi-edge cooperative computing system.

To cope with the inherent challenges mentioned above, we first propose a system-level state evaluation model to express the service-oriented performance and workload of edges at any scheduling period. In this way, the important and differentiated performance characteristics closely related to edge scheduling are preserved, and the heterogeneous configuration of edges can be ignored when making scheduling decisions. Secondly, based on the system-level state evaluation model, we provide a new integer linear programming formulation for the multi-edge cooperation scheduling, which can be a good starting point to inspire solver searching or scheduling algorithms design. Finally, we propose CoRaIS, a reinforcement learning based lightweight real-time scheduler for multi-edge cooperative computing system. Given a high-level goal to minimize the response time of all requests, CoRaIS automatically learns a sophisticated system-level real-time scheduling policy. The policy can be directly generalized to other applications and multi-edge networks.

The main contributions of this paper can be summarized as follows.

- A system-level state evaluation model is built to capture important features closely related to scheduling across edges, including service-oriented performance feature and workload feature.
- The multi-edge scheduling problem is presented as a new integer linear programming formulation, which will support the designing and optimization of scheduling algorithms.
- A lightweight attention-based scheduler (CoRaIS) is proposed to minimize the response time over all requests distributed at edges. The scheduler can provide a high-quality near-optimal solution in real time, irrespective of request arrival patterns and system scales.

II. RELATED WORK

Existing works have explored the formulation and optimization of scheduling problems in the multi-edge or edge-cloud cooperative computing system and gotten some great contributions [11]–[13]. They generally divide dispatched requests into two categories: independent requests and requests with logical execution order, and then design scheduling algorithms respectively.

The efforts [3]–[5], [9], [10], [14]–[17] focus more on independent requests, as well as this paper. However, there are significant differences between these works and this paper in terms of modeling goal, problem settings and optimization approaches. The goal of works [3]–[5], [14] is to maximize
the expected number of requests served per slot with different assumptions. The work [3], [14] assume that the computation requirement and average arrival rate of requests are known, formulates the problem as an integer linear program and prove the problem is generally NP-hard. A heuristic approximation algorithm based on linear program relaxation and rounding is proposed to solve the problem as well. The work [4] builds their own experiment environment that consists of some physical servers and leased clouds, and proposes a coordinated multi-agent actor-critic algorithm for decentralized request dispatch. The algorithm is evaluated on real-world workload traces from Alibaba. Another learning-based scheduling model EdgeMatrix is presented to maximize the throughput while guaranteeing various Service-Level-Agreement priorities in the work [5], where a networked multi-agent actor-critic algorithm to customize resource channels is proposed to improve the system’s stability. The work [15] formulates a request routing problem under the assumptions of computation capacity (i.e. maximum frequency) of a single CPU in the multi-cell mobile edge computing networks, and proposes a randomized rounding algorithm to minimizes the load to cloud. The work [9] assumes that the request arrival at each edge is a Poisson process, the computation requirements (in CPU cycle) of requests follow exponential distribution, and the cloud always has enough computation capacity to provide near-zero computing delay. The work [10] assumes the dynamic arrival of computation requests can be approximated as Poisson process, and the request requires the computing support by a random number of CPU cycles with a finite mean value. The authors transform the scheduling problem into a cooperative queueing game approach to minimize the expected cost of each individual edge server. The works [16], [17] attach to the response time of each request a weight to indicate its latency sensitivity and introduce a machine-dependent processing time in each server. Then the works propose an online scheduling framework based on question and answer (Q&A) mode to minimize the total weighted response time over all requests. There are some other progresses on dispatching requests with logical execution order [6], [7], [18]–[20]. The dependencies among such requests are usually formulated as directed acyclic graphs (DAGs), and the dependency-aware requests scheduling problems are also known as DAG scheduling problem. The work [18] proposes Decima that develops new representations for requests’ dependency graphs and adopts scalable reinforcement learning models to learn work-load-specific scheduling algorithms without any human instruction, in order to minimize average request completion time. The paper [19] allocates computing devices to continuous data flows in a large distributed system, through presenting a graph-aware encode-decoder framework to learn a generalizable resource allocation strategy. The works [6], [7], [20] present how to optimize device placement for training deep neural networks (DNN). The architecture of a DNN model can take as a DAG, and the device placement for DNN is to specify how each operation in a DNN model should be matched to the heterogeneous CPU and GPU devices. The work [20] presents a sequence-to-sequence model that learns to optimize device placement for TensorFlow computational graphs. Spotlight is proposed [6] to find a optimal device placement for training DNNs. Spotlight models the problem as a Markov decision process with multiple stages, and uses a new reinforcement learning algorithm based on proximal policy optimization. A two-level hierarchical model [7] realizes device placement for a neural network with tens of thousands of operations.

In general, the scheduling problem can be taken as a combinatorial optimization problem under some constrains and is proved to be NP-hard. In recent years, designing algorithms to quickly solve combinatorial optimization problems has attracted much attention, and some achievements have been made. The works [21], [22] design learning-based model to solve traveling salesman problems (TSP). The advances [23]–[25] learn policies for vehicle routing problems (VRP). The works [26] propose reinforcement learning based models to solve multiple TSP. The progresses [27], [28] present common framework for combinatorial problems. Solutions for mixed integer programming (MIP) are proposed as well [29], [30].

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. Multi-edge Cooperative Scheduling Processes

The multi-edge cooperative computing system consists of a set of network edges \( \mathcal{E} = \{ e_n \}_{n=1}^N \), and can provide diverse services \( \mathcal{S} = \{ s_k \}_{k=1}^K \). Each edge is under the exclusive management of a single central scheduler, effectively eliminating the possibility of ambiguous scheduling decisions. Furthermore, every edge within the system willingly collaborates with others and entrusts the central scheduler’s decision-making efficacy. Consequently, each edge actively accepts transmitted requests without rejection. This collective commitment ensures a seamless and efficient process, contributing to the overarching goal of achieving timely completion of all tasks. The processes of multi-edge cooperative scheduling are shown in Fig. 2. Before describing the detail processes, we first explain some concepts used in the scheduling process as follows.

![Multi-edge cooperative Scheduling](image_url)
Request: A request usually consists of description text and physical input data. The description text describes the required service, the client ID, etc. Input data is the data to be processed. For example, an image classification request should explain which classifier is required in the description text, and upload the related images as input data.

Request brief: It is a data package that only has some description information of request, without detailed input data. For example, the brief of an image classification request records the size of images and required classifier, and does not include the content of images. By introducing request brief, the data packages used to make scheduling decisions become very small, which would significantly reduce the communication delay among edges and central controller.

Scheduling decision: It contains the information which edge the requests would be executed at. The edges must obey the decision to locally respond to the requests or transfer the requests to other edges.

Then as shown in Fig. 2, the scheduling processes involve seven steps. (i) Clients submit requests and related data to edges. (ii) Edges receive requests and create a request brief for each of them. (iii) Edges submit current service capacity information and the briefs to central controller (CC). (iv) CC makes a scheduling decision based on edge status and request briefs, and designated scheduling algorithms. (v) CC informs edges about the decision, where the execution edge for each request is decided. (vi) Based on the decision, edges determine whether to locally respond to the requests or transmit them to other edges with the relevant data. (vii) The edges feed back the computing results to clients.

B. System Scheduling Decomposition

As the decomposition principle illustrated in Fig. 3, we decompose the multi-edge cooperative system into multiple service-oriented subsystems, where the edges with same service are grouped. For the sake of clarity in the following discussions, we omit explicitly declaring the $s_k$-oriented. However, it’s important to understand that all the operations described can be applied into any service-oriented subsystem.

C. System-level State Evaluation Model

The system-level state evaluation model is inspired by some observations. The first key observation is that there are many popular artificial intelligence services, such as image classification and object detection, exhibiting a functional relationship between their response time and the size of the data packets to be processed. We select the most advance image classification model Model Soups [31] as an example to illustrate the observation, and visualize the relationship of Model Soups in Fig. 4.

In Fig. 4, we can observe that the running time and data size of Model Soups is linearly correlated, and the coefficients of the linear function are related to the configuration of computing devices. The most popular object detection model, YOLOv6 [32], [33] also cares about the computation efficiency. They report the linear relationship between running time and data size for different vision of YOLOv6 when inferring on Tesla T4. Please note, in this paper, we refer to services that have a functional relationship between runtime and data size as ideal services, and our study primarily focuses on this category.

The second observation is that many advanced technologies, such as Docker and Kubernetes, empower one service to create multiple independent replicas on a single device and enable the service to specify the required resources. This reservation mechanism ensures that the resources allocated to each service replica are safeguarded against preemption by other processes, thereby stabilizing the QoS of the service.

Based on these observations, we build our system-level state evaluation model. The model consists of two parts: service-oriented performance estimation and service-oriented workload evaluation.

1) Service-oriented Performance Estimation: Two indicators are used to consistently evaluate the service-oriented performance of edges, that are computation time estimation function ($\phi(x)$) and service replica numbers ($\zeta$). $\phi_k(x)$ is a function that depicts the relationship between the response...
time and the size of data packets to be processed at edge $e_i$, with $x$ denotes the size of the data packets. $\phi_i(x)$ can be approximated by fitting the relationship between data volume and the actual processing time of historical requests, like the fitting operation in Fig. 4. There are some tools that can help establish the relationship, such as numpy.polyfit and scipy.optimize.curve_fit. The hardware configuration also has a significant impact on the execution efficiency, causing $\phi(x)$ to vary across different edges. Fig. 4 illustrates the impact as well. Therefore, when establishing the relationship, only local historical data can be selected. $\zeta_i$ refers to the replica number of the service on edge $e_i$, which is a predefined system-level parameter to support service parallels. A larger $\zeta_i$ indicates edge $e_i$ can deal with more requests in parallel.

By defining $\phi(x)$ and $\zeta_i$, we can focus on considering the primary performance factors of edges while formulating multi-edge cooperative scheduling problem and designing algorithms, and ignore the secondary factors (the heterogeneous hardware configuration and various resource allocation mechanisms to services at edges). Furthermore, with $\phi_i(x)$, we can predict response times on any edge by inputting the request’s data size. This eliminates the need to analyze black box or white box code to obtain the necessary computation numbers for the request and restricts the computing device to the CPU.

2) Service-oriented Workload Evaluation: We design service-oriented queue models for edge $e_i$ to save requests that are at different status, including $Q_{le}^i$ for requests that are waiting for scheduling, $Q_{im}^i$ for requests that will be executed locally, $Q_{out}^i$ for requests that will be transmitted to other edges, $Q_{in}^i$ for requests that will be transferred in from other edges and $Q_{in}^i$ for requests that have been completed. The state transition of requests across queues is presented in Fig. 5.

When evaluating the workload of edge $e_i$, we focus on the requests in $Q_{le}^i$ and $Q_{im}^i$, because only requests in these two queues will make use of the local resources of edge $e_i$. Three features are introduced to evaluate the workloads, including required computing time to complete requests in $Q_{le}^i$ (referred to as $c_{le}^i$), required data transmission time for requests in $Q_{im}^i$ (referred to as $d_{im}^i$), and required computing time to complete requests in $Q_{in}^i$ (referred to as $c_{in}^i$). $c_{le}^i, d_{im}^i$ and $c_{in}^i$ can be evaluated in customized mathematical approximation models. In this paper, we compute them by (1), (2) and (3) respectively. $r$ refers to a request. $\alpha_r$ refers to the data size of request $r$, $\beta_r$ denotes the distance between the source edge of $r$ and edge $e_i$. $C_r$ is a constant to represent the transmission speed for unit data through unit distance. In (1) and (3), we average the computation time required to complete all tasks across multiple copies. As for (2), we make two assumptions based on experience to predict required data transmission time. Firstly, the data transmission time is positively correlated with both data size and transmission distance. Secondly, edges can simultaneously receive data sent by other edges from different ports.

Evaluating the workload before each scheduling operation allows us to obtain the real-time service capacity of edge $e_i$. This real-time system state knowledge is instrumental in making well-informed scheduling decisions.

\begin{align}
    c_{le}^i &= \frac{\sum_{r \in Q_{le}^i} \phi_i(\alpha_r)}{\zeta_i} \\
    d_{im}^i &= \max_{r \in Q_{im}^i} C_r \alpha_r \beta_r \\
    c_{in}^i &= \frac{\sum_{r \in Q_{in}^i} \phi_i(\alpha_r)}{\zeta_i}
\end{align}

D. Problem Formulation

In this paper, the multi-edge cooperative scheduling problem in each SR_k has similar formulation. We firstly define some parameters to formulate the $SR_k$ as $CoMEC = (E, W, \mathcal{V}, \mathcal{P}, \mathcal{I})$. $E = \{e_q\}_{q=1}^Q$ is a set of network edges where $s_k$ is deployed, $|E| = Q$ is the number of edges. $W$ is a $Q \times Q$ matrix that specifies the data transmission distance between any pair of edges, i.e. the entry of $W$ at the $i^{th}$ row and $j^{th}$ column, denoted by $w_{ij} \in \mathbb{R}_+$, is the time cost to transmit one unit data from $e_i$ to $e_j$. For disconnected edge $e_i$ and $e_j$, $w_{ij} = +\infty$. $\mathcal{V} = \{\phi_q\}_{q=1}^Q$ is a set of functions and $\phi_q$ represents computation time estimation function of $e_q$ (explained in the section III-C1). $\mathcal{P}$ is a $Q$-dimensional vector as well. $p_i$ denotes the replica numbers of $s_k$ at $e_i$. $\mathcal{I}$ is a $N \times 3$ matrix that specifies the current workload evaluation of edges. The entry of $\mathcal{I}$ at $j^{th}$ row, denotes as $I_q$, represents the workload evaluation of $e_q$. $I_q = (c_{le}^q, c_{im}^q, d_{im}^q)$ (the definitions are explained in the section III-C2).

The requests distributed in $SR_k$ can be modeled as $CoR = (\mathcal{R}, \mathcal{L}, \mathcal{F}, \mathcal{D})$. $\mathcal{R} = \{r_{z}\}_{z=1}^{|R|}$ is a set of requests that require $s_k$, $|\mathcal{R}| = N$ is the number of requests. $\mathcal{L}$ is a $N \times Q$ matrix, the entry $l_{zq}$ represents whether $r_z$ is located at $e_q$ before scheduling, if yes, $l_{zq} = 1$, else, $l_{zq} = 0$. $\mathcal{F} = \{f_z\}_{z=1}^{|R|}$ is a set that records the size of input data for all $r_z \in \mathcal{R}$. $\mathcal{D}$ keeps the practical related data of requests.

Given $CoMEC$ and $CoR$, let $X \in \{0,1\}^{Q \times \mathcal{R}}$ be a permutation matrix. For $\forall x_{2q} \in X$, $x_{2q} = 1$ represents $r_z$ is dispatched to $e_q$. Then the objective function of multi-edge cooperative scheduling problem can be formulated as (4). The parameter $T_q$ in (4) denotes the required time to complete all requests that are scheduled to $e_q$ as $X$. (4) indicates that the purpose is to get a $X$ that can minimize the response time over
Definition

The transmission distance between edges

The computation time to deal with data of size $r_z$

The computation time to complete backlogs in $Q^{in}_z$

The request $r_z$

The edge $e_q$

The service $k$

Whether $r_z$ is located at $e_q$. $L_q \in \{0, 1\}$

Whether $r_z$ is dispatched to $e_q$. $x_{qz} \in \{0, 1\}$

The input data size of $r_z$ at $e_q$.

The replica number of $e_q$ at $e_q$.

The computation time to complete backlogs in $Q^{in}_z$.

The computation time to complete backlogs in $Q^{in}_z$.

The transmission distance $e_q$ and $e_q$.

A constant to represent the transmission speed for unit data through unit distance.

The remaining transmission time of backlogs in $Q^{in}_z$.

$Z \{1, 2, ..., Z\}$. $Z$ denotes the number of requests.

$Q \{1, 2, ..., Q\}$. $Q$ denotes the number of edges.

TABLE I

THE DEFINITIONS OF PRIMARY NOTATIONS

<table>
<thead>
<tr>
<th>Notation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_z$</td>
<td>The request $z$</td>
</tr>
<tr>
<td>$e_q$</td>
<td>The edge $q$</td>
</tr>
<tr>
<td>$k$</td>
<td>The service $k$</td>
</tr>
<tr>
<td>$L_q$</td>
<td>Whether $r_z$ is located at $e_q$. $L_q \in {0, 1}$</td>
</tr>
<tr>
<td>$x_{qz}$</td>
<td>Whether $r_z$ is dispatched to $e_q$. $x_{qz} \in {0, 1}$</td>
</tr>
<tr>
<td>$t_z$</td>
<td>The input data size of $r_z$ at $e_q$.</td>
</tr>
<tr>
<td>$\phi_q(f_z)$</td>
<td>The computation time to deal with data of $r_z$ at $e_q$.</td>
</tr>
<tr>
<td>$p_q$</td>
<td>The replica number of $e_q$ at $e_q$.</td>
</tr>
<tr>
<td>$c_q$</td>
<td>The computation time to complete backlogs in $Q^{in}_z$.</td>
</tr>
<tr>
<td>$e_q$</td>
<td>The computation time to complete backlogs in $Q^{in}_z$.</td>
</tr>
<tr>
<td>$w_{nq}$</td>
<td>The transmission distance $e_q$ and $e_q$.</td>
</tr>
<tr>
<td>$C$</td>
<td>A constant to represent the transmission speed for unit data through unit distance.</td>
</tr>
<tr>
<td>$t^{in}_q$</td>
<td>The remaining transmission time of backlogs in $Q^{in}_z$.</td>
</tr>
<tr>
<td>$Z$</td>
<td>$Z {1, 2, ..., Z}$. $Z$ denotes the number of requests.</td>
</tr>
<tr>
<td>$Q$</td>
<td>$Q {1, 2, ..., Q}$. $Q$ denotes the number of edges.</td>
</tr>
</tbody>
</table>

all edges and all requests. $T_q$ in (4) can be computed by (5)-(9) with constraints (10) and (11). The definitions of primary notations in the formulation are summarized in Table I.

**obj.** $\min \max_{\lambda \in \mathcal{X}} T_q$

(4)

$\mu_q = \sum_{z \in [Z]} l_{qz} x_{qz} \phi_q(f_z) + e^{in}_q, \forall q \in [Q]$  \hspace{1cm} (5)

$\eta_q = \sum_{z \in [Z]} (1 - l_{qz}) x_{qz} \phi_q(f_z) + e^{in}_q, \forall q \in [Q]$  \hspace{1cm} (6)

$v_q = \max_{z \in [Z]} x_{qz} f_z \left( \sum_{n \in [Q]} l_{zn} w_{nq} \right), \forall q \in [Q]$  \hspace{1cm} (7)

$\kappa_q = \max(C_q v_q, t^{in}_q)$  \hspace{1cm} (8)

$T_q = \max(\kappa_q, \mu_q + \eta_q), \forall q \in [Q]$  \hspace{1cm} (9)

$s.t.$ $\sum_{q \in [Q]} x_{qz} = 1, \forall z \in [Z]$

(10)

$x_{qz} \in \{0, 1\}, \forall z \in [Z], \forall q \in [Q]$  \hspace{1cm} (11)

To be specific, (5) predicts the required computing time to complete all requests that will be executed locally, including previous backlogs and new requests scheduled as $\lambda$. (6) evaluates the required computing time to complete all requests that are transferred from other edges to $e_q$, taking into account both backlogs and new requests scheduled as $\lambda$. (7) predicts the required longest transmission time for data of new requests that are transferred from other edges to $e_q$ as $\lambda$, since multiple edges transmitting data to the same edge in parallel is allowed in our multi-edge cooperative computing system. Considering that the data of backlogs may haven’t been transmitted to $e_q$, we design (8) to estimate the maximum transmission time for all requests that are transferred from other edges to $e_q$, including both backlogs and new requests scheduled as $\lambda$, through max operation over $C_q v_q$ and $t^{in}_q$. Furthermore, due to data transmission and local computing can run simultaneously, and the requests in $Q^{in}_q$ cannot be executed until all relevant data has been received by $e_q$, we design (9) to predict the required response time to complete all requests that are scheduled to $e_q$ as $\lambda$, including backlogs and new requests as well. Here max operation is used to select the case that consumes longer time. While computing a feasible $\lambda$, $\mu_q$ and $\eta_q$ in (10) and (11) must be met to ensure all requests can be scheduled to only one available edge.

Throughout the system’s operation, there will be multiple task scheduling rounds. In each scheduling round, the formulation can be utilized to obtain the optimal solution $\lambda$ based on the current system state $\lambda^{MEC}$ and request state $\lambda^{R}$.

**IV. LIGHTWEIGHT REAL-TIME SCHEDULER DESIGN**

The scheduling problem has been represented as an integer linear programming formulation. There have been some solvers, such as *Gurobi* and *Cplex*, which can accurately solve such problems. However, the search space of multi-edge cooperative scheduling problem is $Q^2$, and it will significantly grow as the number of edges or requests increases. Therefore, getting the optimal solution is theoretically time-consuming. It is necessary to design a novel algorithm that can provide a high-quality solution within a short and predictable time. This paper proposes a lightweight attention-based scheduler called *CoRaiS*, and combines it with reinforcement learning to automatically learn a great policy that helps produce a high-quality scheduling decision in real time.

**A. Architecture of CoRaiS**

*CoRaiS* adopts matching-on-demand (MoD) architecture that consists of two alignment modules (edge encoder and request encoder) and one matching module (context decoder), as presented in Fig. 6. The alignment modules are used to align specific features of heterogeneous edges through multidimensional information exchange. Specifically, the edge encoder embeds and aligns the performance information of edges through multi-head attention mechanism (MHA), and captures the service capacity of multi-edge system by max pooling; the request encoder has similar function with edge encoder, but
works on the requests contexts, i.e. request encoder focuses on capturing and aligning the requirements of requests through MHA, and mastering the global request features by max pooling. The matching module (context decoder) associates the capacity of multi-edge computing system with the requirements of requests through aggregating edges embeddings and requests embeddings, and produces scheduling policies to realize edge matching based on the demands of request.

**Edge encoder:** It is a module to embed edge features. At the beginning of training, input features of edges $f$ are initialized based on the current edge states. To be specific, the input features $f_q$ of $e_q$ include: (i) coordinates $(x_q, y_q)$; (ii) the coefficients of $\phi_q$ and replica numbers $\zeta_q$; (iii) workload evaluation vector $I_q$, and $I_q = (c^e_q, c^m_q, t^m_q)$. The encoder computes initial $d_h$-dimensional edge embeddings $h_q^{(0)}$ through a learnable linear projection with parameters $W_e$ and $b_e$: $h_q^{(0)} = W_e f_q + b_e$. Then the embeddings are updated through $L$ attention layers, which is motivated by Transformer [34] and Attention Model [24]. Each layer consists of two sublayers: a multi-head attention layer (MHA) and an edge-wise fully connected layer (FC). A skip-connection and batch normalization (BN) are also used at each sublayer. The operations are formulated as (12), where $f_q^{(l)}$ denotes the produced edge embedding by layer $l \in \{1, \ldots, L\}$.

\[
\begin{align*}
    f_q^{(l+1)} &= \text{BN}(f_q^{(l)}) + \text{MHA}(\{f_q^{(l-1)}\}_q=1^{Q})) \\
    f_q^{(l)} &= \text{BN}(f_q^{(l-1)}, FC(f_q^{(l)})) \\
\end{align*}
\]

**Request Encoder:** It has similar architecture and operations with edge encoder to embed request features. But the learnable parameters are different. The initial feature $h_z$ of $r_z$ includes (i) coordinates of the source edge of $r_z$; (ii) input data size of $r_z$. The initial features $h_z^{(0)}$ are initialized to a $d_h$-dimensional embeddings by linear projection as (13). Following that, $K$ attention layers are used to update request embeddings. The operations are presented as (14), where $\text{MHA}^k$ and $\text{FC}^k$ are the parameters that are used to embed requests features. The operations of $\text{MHA}^k$ are similar with them in $\text{MHA}^e$.

\[
\begin{align*}
    h_z^{(0)} &= W_r h_z + b_r \\
    h_z^{(k)} &= \text{BN}(h_z^{(k-1)} + \text{MHA}^k(h_z^{(k-1)})_{z=1}^{Z})) \\
    h_z^{(k)} &= \text{BN}(h_z^{(k)}, \text{FC}^k(h_z^{(k)})) \\
\end{align*}
\]

**Context decoder:** The system context comes from the edge embeddings $\{f_q^{(L)}\}_q=1^{Q}$ and request embeddings $\{h_z^{(K)}\}_z=1^{Z}$. Inspired by [22], [35], [36], this paper captures global features $f$ and $h$ by max pooling operation over $\{f_q^{(L)}\}_q=1^{Q}$ and $\{h_z^{(K)}\}_z=1^{Z}$, respectively. Then the new context embedding $c_q^e$ is produced by $\text{MHA}_c$, which has $M$ heads. The computation process through $\text{MHA}_c$ is shown as (15), where $[\ldots, \ldots]$ is the horizontal concatenation operator, $d_y = \frac{d_f}{d_F}$ and $c_q^e$ is the embedding after single attention, and $c_q$ is the final multi-head attention value for context embedding.

\[
\begin{align*}
    f(e_q) &= [f, h, f_q^{(L)}] \\
    x_q &= W_z f(e_q); \ y_z = W_z h_z^{(K)}; \ v_z = W_z h_z^{(K)} \\
    u_z &= \frac{x_q^T y_z}{\sqrt{d_y}}; \ a_q = \frac{e^{u_z}}{\sum_{z=1}^{Z} e^{u_z}} \\
    c_q &= \sum_{z=1}^{Z} W_{c,q} v_z \\
\end{align*}
\]

The MHA operation in context embedding is similar with it in edge encoder and request encoder, but replacing $f(e_q)$ with $f_q^{(l-1)} (h_z^{(k-1)})$ in edge encoder (request encoder).

**Policy generation:** The policy is generated by collecting importance of edges for one request $r_z$ as (16), $\text{imp}_{qz}$ denotes the importance of $e_q$ for $r_z$. $C$ is a constant. To evaluate the probability of edges getting the privilege, softmax is introduced over all edges for each request as (17), where $a_q$ specifies the probability of $e_q$ responding to $r_z$.

\[
\begin{align*}
    p(x_q) &= W_p x_q; \ p(y_z) = W_p y_z; \\
    u_z &= \frac{p(x_q) p(y_z)}{\sqrt{d_y}}; \ \text{imp}_{qz} = C \tanh(u_z) \\
    a_q &= \frac{e^{\text{imp}_{qz}}}{\sum_{q=1}^{Q} e^{\text{imp}_{qz}}} \\
\end{align*}
\]

**B. Training CoRaSiS**

The scheduling probability distribution $p(y|\pi) = \{q_{\pi,z}\}_{\pi \in [Q], z \in [Z]}$ is produced by CoRaSiS, from which we can sample a scheduling decision $\pi$. In order to train CoRaSiS, we define the expectation of the maximum response time of all requests over edges as loss function: $L(\theta|g) = E_{p(\pi)}[L(\pi)]$. Given $\pi$, $L(\pi) = -\hat{\mu}^\pi$ is computed according to (18) and (19). Firstly, a local reward $u_q$ is estimated by (18), where $R_{\pi}^y$ denotes the set of requests to be executed locally and $RT_{\pi}^y$ includes requests that are transferred from other edges to $e_q$ based on the decision $\pi$. $Y(\omega_m, e_q)$ is a function to compute the transmission distance between the source edge $\omega_m$ and the execution edge $e_q$ of $r_m$. The connotation of each equation in (18) is similar with (5)-(9). Then the global reward is formulated as (19).

\[
\begin{align*}
    \mu_q &= \frac{\sum_{m \in RT_{\pi}^y} \phi_q(f_m)}{\zeta_q} + c^e_q \\
    \eta_q &= \frac{\sum_{m \in RT_{\pi}^y} \phi_q(f_m)}{\zeta_q} + c^m_q \\
    \kappa_q &= \max\{\max_{m \in RT_{\pi}^y} f_m Y(\omega_m, e_q), r^m_q\} \\
    \hat{u}^\pi_q &= -\left(\max(\mu_q, \kappa_q) + \eta_q\right) \\
    \hat{u}^\pi_q &= \min_{e_q \in \omega_m} \hat{u}^\pi_q \\
\end{align*}
\]
training realizes more accurate estimation of the policy, decreases training variance and speeds up convergence. Meanwhile, to encourage CoRaIS to sufficiently explore the huge search space, we add an extra entropy loss $H(\theta)$, computed as (20). Then the optimization function can be formulated as (21), where $D$ is the training data set, $C_1$ and $C_2$ are the coefficients.

\begin{align*}
H_\theta(g) &= -\sum_{z=1}^{Z} \sum_{q=1}^{Q} a_{qz}(\theta) \log a_{qz}(\theta) \\
A(\pi_s) &= L(\pi_s) - \frac{1}{S} \sum_{i=1}^{S} L(\pi_i) \\
L(\theta|D) &= E_{g\sim D} \left( C_1 \sum_{s=1}^{S} \log p_\theta(\pi_s|g) A(\pi_s) ight. \\
&\quad \left. - C_2 H_\theta(g) \right)
\end{align*}

We generate synthetic data to build the training dataset $D$ for some reasons. Firstly, even though Alibaba has provided the most prominent cluster dataset, CoRaIS cannot be trained using the dataset, because majority of services in the dataset are related with online shopping applications, which are not ideal services\(^3\) focused on in this paper. Only a few offline services may meet the characteristic of ideal services, but it is difficult to separate them from the dataset. Moreover, the dataset is closely tied to the specific multi-edge cooperative system built by Alibaba, hence, there is uncertainty regarding whether a scheduling policy trained on the dataset would perform well on other multi-edge systems. Secondly, no other datasets containing enough data can be used to train CoRaIS. Thirdly, when generating synthetic data, we can vary the multi-edge cooperative environments and the scheduled services. In this way, the synthetic dataset becomes more comprehensive and better supports CoRaIS in learning a more versatile scheduling policy. To introduce variation of multi-edge cooperative environments, we can vary the number and position of heterogeneous edges, as well as the number of requests submitted to the each edges. To diversify the scheduled services, we can establish different computation time estimation function and service replica numbers (explained in Section III-C1) to express runtime performance of different services.

C. Decode Strategies of CoRaIS

Two decoding strategies are proposed for CoRaIS to generate an effective scheduling decision.

- Greedy decoding: according to the generated policy of CoRaIS, the best execution edge for each request is always selected. That is, for request $r_z^Q$, its execute edge $e_q$ is selected by $q = \arg \max_{q} \{a_{kq}\}_{k=1}^{Q}$.

- Sampling decoding: for request $r_z$, multiple edge selections can be sampled based on multinomial probability distribution over the policy $\{a_{qz}\}_{q=1}^{Q}$, and the best one is reported. A complete scheduling decision entails execution edge selections of requests in the multi-edge computing system.

V. Evaluation

To demonstrate that CoRaIS is able to learn a strong policy and give a real-time decision for the multi-edge scheduling problem, we designs three experiments: conventional test, generalization test, and characteristic validation. Conventional test refers to evaluating the performance of CoRaIS on a dataset that matches the same scale\(^4\) as the one it was trained on. Generalization test refers to evaluating the performance of CoRaIS on a dataset that has large scale than the one it was originally trained on. Characteristic validation is used to assess whether CoRaIS can perceive the workload and heterogeneity of edges, and autonomously implement load balancing.

A. Experiment Descriptions

Instance generation The training and testing datasets are generated as the same rules. Given the number of edges and requests ($Q, Z$), for each edge $e_q$, the coordinates are randomly sampled under the uniform distribution in $(0, 1)^2$; the supported maximum service replica number $r_m$ is randomly sampled in $\{1, 2, 3, 4\}$. The functional relationship between computing time and the size of input data packets is modeled as linear functions\(^5\) for all edges during simulations. Moreover, to represent the heterogeneity across edges, different coefficients are randomly sampled from a uniform distribution within the range $(0, 1)$.

To make CoRaIS can learn to adopt to any initial system-level state, we randomly generate some requests as backlogs for each edge while generating training dataset and testing dataset. The number of backlogs in $Q_x^r$ and $Q_y^r$ of edge $e_q$ are randomly sampled from $(0,100)$. For any backlog $r_x$ in $Q_x^r$, its input data size $f_x$ is uniformly sampled from $[0, 1)$. For any backlog $r_y$ in $Q_y^r$, its source edge $e_k$ is sampled from $[Q] - \{q\}$, and its input data size $f_k$ is uniformly sampled from $[0, 1)$. With these backlogs, the service-oriented workload evaluation are carried out as (1)-(3).

For any new request $r_z$ that will be scheduled in current period, its source edge $e_z$ is sampled from $[Q]$, and the size of related input data $f_z$ is uniformly sampled from $[0, 1)$.

Hyperparameters Learnable parameters are initialized as Uniform$(-1/\sqrt{d}, 1/\sqrt{d})$, with $d$ is the input dimension; learning rate $lr = 1e-5$; batch size is 128, $S = 64$ while using $S$-samples batch RL; $C_1 = 10$ and $C_2 = 0.5$. The edge encoder and request encoder have $L = 5$ and $K = 3$ attention layers, respectively. MHA and FC in two embedding modules same structure, i.e. MHA has 8 heads, FC has one hidden sublayer with dimension 512 and ReLu activation.

\(^3\)We explain ideal services in Section III-C. Ideal services refers to services that has a functional relationship between running time and data size.

\(^4\)In this paper, the scale of dataset refers to the size of the multi-edge cooperative system, including the number of edges in the system and the number of requests submitted to it.

\(^5\)Without loss of generality, we model the relationship using the linear functions. But in practical, other relationships, such as quadratic function, are allowed to train CoRaIS.
**TABLE II**

**Conventional Test Results**

*(Time(s) and Gap: the lower the better. EN and RN denote the number of edges and new requests respectively. 1k=1000. (x%) in the column of Time indicates x% of test instances are resolved. (y) in the column Gap indicates that only successfully resolved instances are counted while computing quality difference.)*

<table>
<thead>
<tr>
<th>Method</th>
<th>EN=5, RN=50 Time(s)</th>
<th>Gap</th>
<th>EN=10, RN=50 Time(s)</th>
<th>Gap</th>
<th>EN=5, RN=100 Time(s)</th>
<th>Gap</th>
<th>EN=10, RN=100 Time(s)</th>
<th>Gap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gurobi(10s)</td>
<td>0.3592</td>
<td>1</td>
<td>0.3473</td>
<td>1</td>
<td>0.6542</td>
<td>1</td>
<td>3.4865</td>
<td>1</td>
</tr>
<tr>
<td>Gurobi(1s)</td>
<td>0.3252</td>
<td>1</td>
<td>0.3373</td>
<td>1</td>
<td>0.1252</td>
<td>1.0001</td>
<td>0.4921</td>
<td>1.0001</td>
</tr>
<tr>
<td>Local</td>
<td>-</td>
<td>2.1712</td>
<td>-</td>
<td>2.8032</td>
<td>-</td>
<td>1.8594</td>
<td>-</td>
<td>2.7055</td>
</tr>
<tr>
<td>Random(1)</td>
<td>-</td>
<td>2.1987</td>
<td>-</td>
<td>2.8023</td>
<td>-</td>
<td>1.9198</td>
<td>-</td>
<td>2.759</td>
</tr>
<tr>
<td>Random(100)</td>
<td>-</td>
<td>1.2916</td>
<td>-</td>
<td>1.8148</td>
<td>-</td>
<td>1.2732</td>
<td>-</td>
<td>1.7422</td>
</tr>
<tr>
<td>Random(1k)</td>
<td>-</td>
<td>1.2916</td>
<td>-</td>
<td>1.6282</td>
<td>-</td>
<td>1.1863</td>
<td>-</td>
<td>1.5854</td>
</tr>
<tr>
<td>FC1-CoRaiS(greedy)</td>
<td>0.0050</td>
<td>3.1129</td>
<td>0.0052</td>
<td>4.638</td>
<td>0.0052</td>
<td>3.346</td>
<td>0.0052</td>
<td>5.3293</td>
</tr>
<tr>
<td>FC2-CoRaiS(greedy)</td>
<td>0.0051</td>
<td>4.0758</td>
<td>0.0051</td>
<td>5.7307</td>
<td>0.0052</td>
<td>4.4914</td>
<td>0.0051</td>
<td>7.8728</td>
</tr>
<tr>
<td>FC3-CoRaiS(greedy)</td>
<td>0.0051</td>
<td>4.0758</td>
<td>0.0052</td>
<td>5.7307</td>
<td>0.0053</td>
<td>4.4914</td>
<td>0.0051</td>
<td>7.8728</td>
</tr>
<tr>
<td>CoRaiS(greedy)</td>
<td>0.0051</td>
<td>1.0783</td>
<td>0.0052</td>
<td>1.0953</td>
<td>0.0052</td>
<td>1.0450</td>
<td>0.0051</td>
<td>1.1083</td>
</tr>
<tr>
<td>FC1-CoRaiS(100)</td>
<td>0.0051</td>
<td>1.4118</td>
<td>0.0051</td>
<td>1.8141</td>
<td>0.0052</td>
<td>1.2704</td>
<td>0.0051</td>
<td>1.7481</td>
</tr>
<tr>
<td>FC2-CoRaiS(100)</td>
<td>0.0051</td>
<td>1.4131</td>
<td>0.0052</td>
<td>1.8163</td>
<td>0.0051</td>
<td>1.2703</td>
<td>0.0052</td>
<td>1.7491</td>
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<tr>
<td>FC3-CoRaiS(100)</td>
<td>0.0051</td>
<td>1.4124</td>
<td>0.0052</td>
<td>1.8182</td>
<td>0.0052</td>
<td>1.2704</td>
<td>0.0051</td>
<td>1.7463</td>
</tr>
<tr>
<td>CoRaiS(100)</td>
<td>0.0051</td>
<td>1.0221</td>
<td>0.0052</td>
<td>1.0267</td>
<td>0.0052</td>
<td>1.0091</td>
<td>0.0051</td>
<td>1.0361</td>
</tr>
<tr>
<td>FC1-CoRaiS(1k)</td>
<td>0.0050</td>
<td>1.2956</td>
<td>0.0052</td>
<td>1.6274</td>
<td>0.0052</td>
<td>1.1837</td>
<td>0.0053</td>
<td>0.8769</td>
</tr>
<tr>
<td>FC2-CoRaiS(1k)</td>
<td>0.0051</td>
<td>1.2913</td>
<td>0.0052</td>
<td>1.6269</td>
<td>0.0052</td>
<td>1.1857</td>
<td>0.0051</td>
<td>1.5858</td>
</tr>
<tr>
<td>FC3-CoRaiS(1k)</td>
<td>0.0051</td>
<td>1.2929</td>
<td>0.0051</td>
<td>1.6276</td>
<td>0.0052</td>
<td>1.1856</td>
<td>0.0051</td>
<td>1.5851</td>
</tr>
<tr>
<td>CoRaiS(1k)</td>
<td>0.0051</td>
<td>1.0148</td>
<td>0.0052</td>
<td>1.0186</td>
<td>0.0052</td>
<td>1.0069</td>
<td>0.0051</td>
<td>1.0297</td>
</tr>
<tr>
<td>Gurobi(0.005s)</td>
<td>(44.81%)</td>
<td>(1.7981)</td>
<td>(19.69%)</td>
<td>(2.6884)</td>
<td>(6.02%)</td>
<td>(1.184)</td>
<td>(5.46%)</td>
<td>-</td>
</tr>
<tr>
<td>Gurobi(0.01s)</td>
<td>(83.82%)</td>
<td>(1.2584)</td>
<td>(45.91%)</td>
<td>(2.0371)</td>
<td>(34.91%)</td>
<td>(1.3904)</td>
<td>(3.40%)</td>
<td>-</td>
</tr>
<tr>
<td>Gurobi(0.05s)</td>
<td>0.0886</td>
<td>1.0009</td>
<td>0.0886</td>
<td>1.0026</td>
<td>0.0629</td>
<td>1.0013</td>
<td>0.1211</td>
<td>1.0334</td>
</tr>
</tbody>
</table>

---

**CoRaiS** is trained from 40000 batches on the device with 2×Intel(R) Xeon(R) Gold 5215 CPU that can provide 40 processors and 2×NVIDIA GTX 2080Ti, and CoRaiS uses Adam optimizer, PyTorch 1.11 framework and python 3.8 on Ubuntu 18.04.

**Baselines** It must be mentioned that as our best knowledge, CoRaiS is the first artificial intelligence based work that breaks many assumptions of prior works, deals with a multi-edge computing system where every edge is allowed to receive requests from clients, and optimizes an objective function that minimize the responding time over all requests. In order to evaluate the performance of CoRaiS, the results generated by CoRaiS are compared with that produced by exact solver (Gurobi). Gurobi is able to help calculate exact solutions. Meanwhile, we propose two heuristic approaches (Local and Random) as the heuristic baselines in the scenario. Three learning-based baselines are designed as well.

- **Exact baseline**: Gurobi is one of the state-of-the-art solver for integer linear programming problems. However, Gurobi may fall into long-term calculation due to the huge search space of multi-edge scheduling. Therefore, it is necessary to give a computation time limitation (∏ s).
- **Heuristic baselines**: two algorithms are used to provide heuristic baselines. (i) **Local**: executing all requests at their source locations. (ii) **Random**: randomly sampling the execution edges for all requests. It is allowed to sample multiple times and report the best one.
- **Learning-based baselines (ablation studies for aligning modules of CoRais)**: three synthetic neural network models are used to illustrate the effectiveness of CoRaiS. (i) **FC1-CoRaiS**: replacing multi-head attention aligning mechanism of edge encoder in CoRaiS with multi-layer perceptron, and maintaining the same number of neuron parameters. (ii) **FC2-CoRaiS**: adopting the similar MoD architecture with CoRaiS, but using multi-layer perceptron to replace the multi-head attention aligning mechanism in request encoder. (iii) **FC3-CoRaiS**: adopting MoD structure, but without aligning mechanisms in both edge encoder and request encoder, only using multi-layer perceptron to embed edges features and requests features. Since FC1-CoRaiS, FC2-CoRaiS and FC3-CoRaiS adopt the similar MoD architecture and have the same input/output with CoRaiS, they are able to use the same decoding strategies with CoRaiS as well.

**Performance indexes** Two indexes are used to evaluate performance. (i) **Time(s)**: time taken to make scheduling decisions, because the multi-edge cooperative computing system needs an approach that can provide a real-time scheduling decision. (ii) **Gap**: quality difference of solutions that are generated by CoRaiS and other baselines, compared with the solution generated by Gurobi(10s) in the same instance. Solutions from Gurobi(10s) are considered as the optimal benchmark in the simulations. The gap is computed by (22). ∏ includes CoRaiS and other baselines. ∏ signifies the best solution obtained from the specific approach b (b ∈ ∏). ∏ refers to the best solution generated by Gurobi(10s). L(π) refers
to the predicted response time for all requests in the multi-edge cooperative computing system, and $L(\pi)$ is computed by (19). The gap is critical because the multi-edge cooperative computing system also require the real-time approach to produce a high-quality solution.

$$gap_\pi = \frac{L(\pi | b)}{L(\pi | \text{Gurobi}(10s))}, \forall b \in \mathbb{N}$$ (22)

### B. Results Analysis

1) Analysis of Conventional Test Results: CoRaiS is a lightweight model that has about 4 million learnable parameters. We trained CoRaiS on four scales: (EN=5, RN=50), (EN=5, RN=100), (EN=10, RN=50) and (EN=10, RN=100). EN and RN denote the number of edges and requests respectively. The models occupy 1511M, 1961M, 1539M, and 2057M on a single GTX 2080Ti GPU during training. We test the performance of learned policies on the same scale problems, and the results are shown in Table II.

(i) Gurobi can quickly obtain the optimal solutions for small-scale problems, and the average time costs for (EN=5, RN=50), (EN=5, RN=100) and (EN=10, RN=50) are less than 1s. However, as the problem scale becomes larger, such as (EN=10, RN=100), the solving time increases significantly, even sometimes, Gurobi spends 10s but only get a sub-optimal solution.

(ii) The solutions generated by Gurobi(1s, 10s) are very close. In practice, Gurobi usually uses branch and bound to solve problems. Sometimes it can quickly get a good non-optimal solution, but it will keep exploring in the search space because it wants to obtain a better solution. Therefore, it is difficult to predict the computing time required by Gurobi to get a high-quality solution.

(iii) Heuristic approaches (Local and Random) take near-zero time to give a solution, but the quality is far away from the optimum.

(iv) The solving time taken by CoRaiS(greedy, 100, 1k) is close to 0.005s, which is much less than Gurobi. The gap closing to 1 shows CoRaiS successfully learns an efficient policy that helps produce high-quality solutions. Therefore, CoRaiS has potential to provide real-time and high-quality decision to support efficient operations of the multi-edge cooperative computing system.

(v) CoRaiS and other three learning-based models (FC1-CoRaiS, FC2-CoRaiS and FC3-CoRaiS) adopt the same decoding strategies (greedy, sampling). The comparison results show that the two alignment mechanisms of edge/request features play important roles in promoting policy learning.

(vi) Because CoRaiS spends near 0.005s on solving the problems, we explore the performance of Gurobi(0.005s) as well. The experimental results illustrate that it is very difficult for Gurobi to solve the problem within such a short time,
even to calculate an approximate solution. Then we relax the time
costs to 0.01s and 0.05s. The results generated by
Gurobi(0.01 s) show that double relaxation does not improve
performance much. The proportion of problems that are not
solved approximately is still high. Some simple problems can
obtain near-optimal solutions, but the solutions are much far
from the optimum. The results generated by Gurobi(0.05s)
shows 10X relaxation helps a lot, since all problems get their
sub-optimal solutions. However, the practical calculation time
to solve the problems is usually longer than the constraint, such as
0.0886s for (EN=10, RN=50) and 0.1211s for (EN=10, RN=100), which indicates that Gurobi cannot precisely control
the solving process according to time constraints, the solving
time is still uncontrollable. Moreover, even if the time con-
straint is relaxed by 10 times, the performance still shows sig-
nificant degradation when encountering large-scale problems,
such as the average gap is 1.0334 for large-scale problems
(EN=10, RN=100), while the average gap is 1.0009 for small-
scale problems (EN=5, RN=50). Compared with that, CoRaiS
stabilized the solving time consumption at 0.005s, meanwhile,
the gap increasing from 1.0148 to 1.0297 keeps relatively stable.

2) Analysis of Generalization Test Results: We train
CoRaiS on instances under problem scale setting(EN=10,
RN=100). The learned model is directly applied into larger-
scale instances. The results are presented in Table III.
Gurobi(10s) takes a long time (> 2s for average) to compute a
good solution and its time cost increases as the problem scale
becomes larger, from 2.8s for (EN=10, RN=200) to 7.2s for
(EN=50, RN=800). Compared with Gurobi(10s), CoRaiS costs
a shorter time (< 0.02s) to obtain a high-quality near-optimal
solution by sampling, and its time cost does not increase
significantly, from 7ms for (EN=10, RN=200) to 16ms for
(EN=50, RN=800), even though the problem scale becomes
20 times larger. We force Gurobi to provide solutions within
(< 0.01s) and (< 0.02s) respectively, to check whether it can
get similar performance with CoRaiS. The results presented
in Table III show that Gurobi can hardly solve large-scale
problems within a short time. Then we relax the time limitation
to 10 times, i.e. 0.2s, the comparison results show that only a
few large-scale problems can be solved.

Sampling decoding effect We found that sampling more
from the policy generated by CoRaiS can improve the solution
quality while slightly increasing computation time (at 0.0001s
level), the experimental results are presented in Fig. 7. It
indicates that CoRaiS has the potential to be applied to other multi-edge cooperative computing systems, regardless of their scale, since CoRaiS is capable of generating high-quality solution in real-time through sampling.

3) Analysis of Characteristic Validation Results: (i) Load balancing (LB): We design five homogeneous edges and push same backlogs on them, so that the initial system-level state of edges are same, and the time of edges responding to backlogs satisfies $b_E = b_D = b_C = b_B = b_A$. Then we conduct 10k experiments on the system. In each experiment, 100 same requests are submitted to $e_A$, and CoRaiS is used to provide a scheduling solution. The results are presented in Table IV(LB). One randomly sampled case shown in Fig. 8 is used to visualize the CoRaiS scheduling results. The number of requests executed at five edges are approximately equal, and the response time are very close. Therefore, we claim that CoRaiS learned to optimize scheduling through load balancing without manual intervention.

(ii) Workload perception (WP): We design five homogeneous edges and induce differences in response time to backlogs by pushing different numbers of requests to each edge, so that the initial system-level state of edges are different. The time of edges responding to backlogs satisfies $b_E \leq b_D \leq b_C \leq b_B < b_A$. Then 10k experiments submitting 100 requests to $e_A$ are conducted. CoRaiS makes decisions to schedule requests. As shown in Table IV(WP), the number of requests to be dispatched to each edge is different and follows the order $n_E \geq n_D \geq n_C \geq n_B > n_A$ on average. Meanwhile, there is no significant difference in response time after scheduling. Fig. 9 visualizes a case to illustrate the workload perception of CoRaiS. In this case, since $e_A$ has much heavier original workload than other edges, it keeps a small amount of the newly arrived requests and diverted most of them to speed up the completion of all requests. Therefore, we claim CoRaiS is able to perceive workload of edges while scheduling.

(iii) Heterogeneity awareness (HA): We design five heterogeneous edges, that is, the computation time estimation functions of edges are different. We arrange the computing performance of edges in the order of $E > D > C > B > A$. Then we equalize the response times of the edges to backlogs by adjusting the number of requests. After that, 10k experiments are conducted. In each experiment, 100 same requests are submitted to $e_A$, and CoRaiS is used to provide a scheduling solution. According to the results in Table IV(HA), the more powerful edge serves more requests, and the corresponding response time of all edges are very close. We visualize a randomly sampled illustration in Fig. 10 as well. In this case, $e_E$ responds to the most requests while $e_A$ achieves the fewest, because the computation performance of $e_E$ is much more powerful than that of $e_A$. With CoRaiS scheduling, the variance of estimated responding time of such five edges is very small. Therefore, we claim CoRaiS is able to recognize heterogeneity while cooperating multi-edges.

Fig. 10. A case to demonstrate that CoRaiS is able to recognize heterogeneity when cooperating multiple edges. In this case, the computing performance of five heterogeneous edges follows the order $E > D > C > B > A$, and the response times of the edges to their backlogs are same.

VI. Conclusion

The system-level state evaluation model is introduced in this paper, to shield edges heterogeneity in hardware configuration and redefine the service capacity at edges. After that, an integer linear programming formulation is presented for the multi-edge scheduling problem. CoRaiS, a learning-based lightweight real-time scheduler, is proposed to minimize the response time over all distributed arriving requests. The experimental results demonstrate that CoRaiS successfully learned a strong policy to make high-quality scheduling in real time, irrespective of request arrival patterns and system scales.

References


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