# R2: A Distributed Remote Function Execution Mechanism With Built-In Metadata

Jianpeng Qi<sup>D</sup> and Rui Wang<sup>D</sup>, Member, IEEE

Abstract-Named data networking (NDN) constructs a network by names, providing a flexible and decentralized way to manage resources within the edge computing continuum. This paper aims to solve the question, "Given a function with its parameters and metadata, how to select the executor in a distributed manner and obtain the result in NDN?" To answer it, we design R2 that involves the following stages. First, we design a name structure including data, function names, and other function parameters. Second, we develop a 2-phase mechanism, where in the first phase, the function request from a client-first reaches the data source and retrieves the metadata. Then the best node is selected while the metadata responds to the client. In the second phase, the chosen node directly retrieves the data, executes the function, and provides the result to the client. Furthermore, we propose a stop condition to intelligently reduce the processing time of the first phase and provide a simple proof and range analysis. Simulations confirm that R2 outperforms the current solutions in terms of resource allocation, especially when the data volume and the function complexity are high. In the experiments, when the data size is 100 KiB and the function complexity is  $\mathcal{O}(n^2)$ , the speedup ratio is 4.61. To further evaluate R2, we also implement a general intermediate data processing logic named "Bolt" implemented on an app-level in ndnSIM. We believe that R2 shall help the researchers and developers to verify their ideas smoothly.

*Index Terms*—Edge computing, metadata, information-centric networking, named-data networking, decentralized method invocation.

# I. INTRODUCTION

DC ESTIMATES that by 2025 41.6 billion devices will be interconnected, and data volume will reach 79.4 zettabytes (ZB) [1]. Current cloud computing architectures do not afford such an overwhelming amount of devices and data due to high latency, limited bandwidth, high carbon footprint, and poor security [2]. Many traditional services that are processed in the cloud but generated remotely [3] are thus maintained at a

Jianpeng Qi is with the School of Computer and Communication Engineering, University of Science and Technology Beijing, Beijing 100083, China.

Rui Wang is with the School of Computer and Communication Engineering, University of Science and Technology Beijing, Beijing 100083, China, and also with the Shunde Graduate School of University of Science and Technology Beijing, University of Science and Technology Beijing, Foshan 528000, China (e-mail: wangrui@ustb.edu.cn).

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Rice DC Cloud WAN Edgs Base station WIFI AP End-devices

Fig. 1. Illustration of edge computing [6].

high cost, e.g., the communication and computation-intensive tasks, such as image recognition and target tracking. Thus, edge computing, an accelerator of cloud computing, affords better computing resources for users and thus gains widespread attention. Current edge computing features, i.e., ultra-low latency, geographical distribution, unlimited bandwidth, high privacy, and security, offset the lack of cloud computing and employ it used in many realms [4]. Additionally to the edge resources, as illustrated in Fig. 1, "edge computing includes employing networked resources closer to the data sources/sinks. Resources can be at the edge, in the cloud, and everywhere in between a continuum" [2], [5], [6]. Hence, edge computing affords task processing and data analysis everywhere.

Edge resources, specifically the continuum, are usually employed to execute tasks in a distributed manner to provide a time-limited service. For example, developers may partition the communication and computation-intensive deep learning models, consecutively deploy them on the continuum, and then execute them to obtain the results with a short delay [7]. Compared with purely cloud processing, continuum processing has several benefits: low energy cost and low latency. However, the latter advantages assume that the nodes/networks state and the data sources details are known, even for a trivial counting job, such as task scheduling, resource discovering, and data retrieving. The most popular way of knowing and managing these states and details is utilizing a central metadata server that involves abstract data about essential attributes such as location, size, and format. This strategy is used in many applications like the "Metastore" or "NameNode" of Apache Hadoop. By managing the metadata through the central node, the developers or users can easily leverage their resources.

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Nevertheless, in an edge computing scenario, metadata management is non-trivial, as developing such a central server is costly. This is because enormous small data pieces, chunks, and files, are scattered in geo-graphical distribution, and gathering and managing them in a centralized manner becomes infeasible, as the nodes within the continuum are usually volatile, highly changeable, and even unreliable [8], [9]. Electing a consensus node with high availability in such a dynamic environment imposes high scheduling and maintenance costs [10], prohibiting edge computing from being affordable. Furthermore, cost estimation, monitoring the remote nodes' status, authentication, and service optimization is challenging. Therefore, utilizing the edge resources in a decentralized and native way instead of a consensus node becomes critical.

Some typical applications like CDN and DNS accelerate the network's data access speed. Specifically, CDN caches offer little in terms of general computational capabilities [11], while DNS [12] introduces additional inevitable name resolution delays [9]. Nevertheless, the current IP architecture suitable for point-to-point communication is limited in distributed networks [13].

Fortunately, Information-Centric Networking (ICN) and, in particular, its prominent Named Data Networking (NDN) instantiation [13] that constructs the network based on the data name rather than IP provides a realistic solution. Specifically, the work based on NDN uses the function/service name as its routing rules to find the proper executor in a fully distributed manner. This strategy affords to provide quickly and efficiently several scalable and robust services, e.g., serverless computing, function as a service, and in-network computing [14], [15], [16]. However, ICN/NDN technology is still at an early stage and requires more investigation [17].

Many works that integrate the function or service name and directly transmit the raw data to the executor may cause a blocking problem. Thus, metadata should solve the latter issue before accelerating the edge computing speed. Besides the proper executor selection, retrieving metadata as the first step presents several side benefits, such as checking the node's health or working status in the data forwarding path, affording cost estimation by relatively small metadata to avoid network congestion, and warming up the dependent environment of the function/service.

Nevertheless, the following question arises, "is it feasible to perform in-network processing in NDN according to the metadata?". To answer this question, this paper investigates leveraging resources within the continuum in a distributed fashion to satisfy the function/service requirement in NDN. The proposed design presents the following features: (1) Data and metadata are distributively stored, with the preferred location being the data producer. (2) The user publishes an Interest containing a data name and a function with parameters and only expects the function result (output of the function). (3) The function can be executed along the continuum from the user to the data generator. (4) Most importantly, using metadata to select the best function execution node to minimize the end-to-end delay. Based on these features, we propose a 2-phase distributed remote function execution mechanism utilizing metadata. During the first phase, we select the best executor in the forwarding path according to the data abstract, node status, and network condition to minimize the total end-to-end delay. Then, in the second phase, we use this executor as a "transit station" to receive the large raw dataset, analyze it, and send the short analyzed result to the requester. We verify this idea on the NDN project [13], while most codes are implemented on an app-level to make R2 computing scalable. Since the user only cares about the result, we name our method "Request Result" ("R2"). The major contributions of this work are as follows:

- We propose R2 to prove the feasibility of distributively running the function based on metadata. R2 assumes the metadata is stored together with its data and utilizes a 2-phase mechanism to consecutively complete the metadata extraction, cost estimation, function executor selection, data extraction, function execution, and result response.
- 2) To find the best node for function execution, we formulate a distributive cost estimation process based on metadata combined with a stop condition. This strategy avoids scanning all nodes along the forwarding path to reduce the result retrieving time automatically. The stop condition can also be used in other uncertain edge computing scenarios to distributedly select the best node.
- 3) We implement, evaluate and analyze the performance of R2 on ndnSIM [18], involving numerous experiments conducted on a real-world network topology dataset. Additionally, to make R2 flexible and portable, we developed an application-level intermediate data processing plugin named "Bolt", which can be installed on a computing-capable node to make R2 scalable. R2 is open source and can be found on GitHub [19].

The remainder of this paper is as follows. Section II presents the related work on computing within the continuum. Then Section III introduces some preliminaries of NDN and the details of the R2, including name format, forwarding pipeline, cost optimization, applied scenes, and proofs. Section IV discusses the experiments, numerical results, and the "Bolt" implementation, while Section V discusses some security issues. Finally, Section VI concludes this paper.

## II. RELATED WORK

Executing functions within the continuum is a well studied topic in many realms, such as in-network caching [23], in-network computing [24], software-defined networking (SDN) [25], and network function virtualization (NFV). ICN is a straightforward way of forwarding the users' interest without a centralized coordinator and considering name resolving, and thus in this paper, we focus on the related work utilizing ICN. Table I compares the notable related works regarding the implementation level of the forwarding strategy, the function executing logic, and the selection of the function/service executor. It should be noted that, in addition to the comparable items in Table I, our work provides a simple distributed way

 TABLE I

 COMPARISON WITH THE NOTABLE RELATED WORKS

Work <sup>1</sup>	Forwarding strategy	Executing level	Distributed executor selection	Executor selection space <sup>2</sup>	
NFaaS [20]	Custom	NFD	None (Service duplicating)	A∩E	
RICE [16]	Builtin	Арр	None	Producer	
CFN [21]	Builtin	Арр	Moderate (Task scheduler)	$A \cap E$	
NDNe [22]	Builtin	NFD	Distributed (Replies first)	A∩E	
IoT- NCN [17]	Custom	NFD	Distributed (Piggyback- ing)	$P \bigcap E$	
ICedge [15]	Custom	Арр	Distributed (Monitoring metrics)	A∩E	
[9]	Custom	Арр	Distributed (Monitoring metrics)	A∩E	
R2	Custom	Арр	Distributed	$P \cap E$	

1. **A**: Nodes matched the given name (prefix); **E**: Nodes that can execute the function; **P**: Nodes on the forwarding path.

2. CFN, NDNe, ICedge, and [9] send the function name to the executor at first.

to check the existence of the requested data instantly and minimize the end-to-end delay by using metadata.

Combining ICN and edge computing has inspired many in-network processing works. According to their design goal, these works can be generalized into either service routing or best node selection. Routing function/service according to the name, such as Named Function as a Service (NFaaS) [20] and NDNe [22], can support many edge-native services. Thus, NFaaS and NDNe are typical serverless computing methods allowing cloud computing to jump into edge computing, where instead of a centralized metastore, the function name is employed to fabricate a decentralized service network. This strategy affords a more scalable and flexible distributed network using the function name as its routing policy. Michał et al. propose a 4-way handshake remote method invocation (RICE) [16] in NDN. In RICE, the consumer first sends a function Interest (I1) carrying a handshake identifier to the producer that runs the function and creates a reverse path from the producer to the consumer. Second, when the producer receives I1, it creates an Interest (I2) containing the received identifier, following the previously established reverse path towards the client. Third, the client responds and sends the parameters (D2) after receiving I2. At last, the producer executes the function with its input parameters D2 and responds to the result (D1) concerning I1. By integrating a 4-way handshake design, RICE solves several issues, including timer and privacy concerns. However, it is not handled how to select the proper node to run the function.

Memory and computing capacity decrease as we descend levels within the continuum and move closer to the client [26]. Thus, selecting the best node is vital within the continuum,



Fig. 2. Reference network topology.

especially for critical applications. Michał *et al.* further propose the Compute First Networking (CFN) scheme that relies on RICE to solve the node selection issue [21]. Forwarding in the store-and-forward network like NDN affords the same function to be cached everywhere. Thus, "compute reuse" can also be utilized to avoid re-computing the same tasks in a multi-user scenario [15]. Amadeo *et al.* [17] propose an IoT-Named Computation Networking (IoT-NCN) framework. This method estimates the service cost by *piggybacking* a SERVICEEXECCOST field in the Interest and updates the SERVICEEXECCOST value in a distributed manner. After the Interest reaches the last edge node, an *executor acknowledgment* is sent back to finish the best executor election.

However, in a data-centric network, we argue that the data name should also be a component of the Interest name. Most of the above-mentioned service-oriented methods, except for IoT-NCN, assume the routing strategies rely on the function name rather than the data name, which is not capable of generalizing the case where data is stored on the other edge node. At least additional Interest needs to be sent. IoT-NCN [17] adds the data name in the Interest in front of the function name and routes it to the last edge node on the IoT domain to create data-oriented distributed services. However, its cost estimation does not integrate with metadata, i.e., it is ineffectual to the actual data size and type, especially for other data analytic applications.

Unlike current works, R2 overcomes the challenges mentioned above by utilizing 2-phase operations with metadata. R2 uses the data name as its forwarding strategy to satisfy the data-oriented applications and metadata to enhance the best node selection accuracy.

## III. R2

This section first provides the reference topology illustrated in Fig. 2. This topology is tangible, especially in a cross-edge analytic area [27], where the backbone router can represent an edge site covering a city or a town, and the gateway can be an edge server covering a community or a home. The available computing (bandwidth) capacities of these nodes (links) decrease (increase) as we descend levels and move closer to the end device [26]. We assume the data with their metadata are commonly stored in the end device. It is worth noting that due to the ISP barrier, the number of hops between the two mutually reachable end devices in different neighboring cities can be significant [28]. Thus, it is mandatory in such an unstable environment to find the best node within the continuum to perform the user's function.

Section III-A provides some NDN preliminaries and a straightforward example to clarify our ideas. Then, we give an elucidation of the R2 process (Section III-C), including name structure (Section III-B), cost model and the best node selection (Section III-C.1), the stop condition of reducing delay (Section III-C.2), proofs, and some analysis (Section III-C.3).

## A. NDN Preliminaries

As a concrete architecture of ICN, the NDN project [13] aims to solve the communication network problem. In a communication network (e.g., IP network), packets are namedonly endpoints, and thus it is hard to apply them to the edge computing area where numerous devices exist. Instead of IP, NDN uses the Name concept to fabricate the network among different nodes. This architecture contains two basic network data packets, Interest and Data. An Interest packet comprises the Name of the requested data and other options defined by the requester. Data consists of the data Name, data contents, signature, and other user-defined information. When a user (also called consumer in NDN) retrieves the data, he first sends an Interest packet into the network. Then the NDN forwarder (NDN Forwarding Daemon, NFD) enters the forwarding pipeline to redirect Interest toward the data producer according to the Interest name. Finally, the producer responds to the requested data back to the consumer. The consumers drive communication in NDN, i.e., a receiverdriven communication mode. Other techniques, e.g., session support [9], [29], and Long-Lived Interest, can also ease data pushing from the producer.

The NDN design assumes hierarchically structured names. For example, it retrieves the camera stream or the file remote-monitor-data stored in Alice's home through NDN to give a further analysis like confirming her baby is safe. The Name of Interest might be /alice's-home/remote-monitor-data, where / delineates name components in text representations. Each node in NDN first checks its Content Store (CS), then Pending Interest Table (PIT) and Forwarding Information Base (FIB), and finally redirects this Interest by the Forwarding Strategy to the data node located at Alice's home.<sup>1</sup> This process is commonly adopted in a longest-prefix matching method.

An example. Recently, many homes where families have babies or are feeding pets have installed several types of systems to monitor and control their security devices remotely (using a smartphone and an app). These systems usually contain machine/deep learning models to provide intelligent computation and communication-intensive services such as fall detection, fire warning, and home security checking. Some



Fig. 3. Interest name structure.

systems may need time to identify the most critical event, e.g., the alarm system. A common feature of these jobs is the a priori known dataset schema, as different schemas typically have different processing logic. In Alice's example, the camera types and video format can be different, such as 60 fps at 12K, 110 fps at 8K, or 220 fps at 4K. Hence, different function adaptors are needed during runtime. In addition to data schema, data size is another vital indicator of the service delay (in Alice's example, the data volume is enormous). Transmitting these massive HD video streams identified by /alice's-home/remote-monitor-data on the entire network could be challenging for the backbone and Alice's internet expenditure.

Indeed, Alice cares about her baby's position, and thus, we need to find a trusted node<sup>2</sup> to identify or analyze the baby's status, i.e., get the baby's position or extract one picture having the baby by running a detect function in the HD video with a short delay. Finding the node requires the metadata of the remote-monitor-data, such as the data size, format, and resolution. This information assists in making a more accurate and fast choice on minimizing the analysis delay before transmitting the large file. In this case, metadata content can be in a JSON format {resolution:12k, filetype:AVI, size:12MiB}, with the attribute size being the most important. Furthermore, some devices have flashcards that are incapable of storing the entire dataset, and thus additional hard disc I/O operations are involved. Nevertheless, metadata information can help us avoid these devices.

Next, according to Alice's example, we give the name structure in R2.

## B. R2 Interest Name Structure

Following Alice's example as mentioned before, Fig. 3 depicts the entire Interest Name in R2.

Name in Fig. 3 means finding the data that named by /alice's-home/remote-monitor-data and obtaining the baby's position by running the detect function. It starts with a prefix /r2 identification used to avoid mixing with the traditional NDN Interest. Then, we place the /alice's-home/remote-monitor-data components behind /r2 to let NFD daemons find the camera in Alice's home. We put the function component /detect behind data-name and separate them with /sep. Component {object = baby, action = position} involves the ApplicationParameters of NDN Interest

<sup>&</sup>lt;sup>1</sup>CS is a container to store Data packets, PIT is a list to store the unsatisfied Interest packets, FIB is a routing table which maps Name components to next hops, and Forwarding Strategy is a series of policies and rules about forwarding Interest and Data packets.

<sup>&</sup>lt;sup>2</sup>A series of trusted nodes can be selected by many techniques such as blockchain consensus, secure multi-party computation, or manually deploying authentication services in advance.

Remark: Name matching strategies of NFD usually recognize the Interest by the data name in a "Longest Prefix Match" fashion. Here the data name is /alice's-home/ remote-monitor-datanot/r2. This difference is solved by the proposed "Bolt" and a custom Strategy. Other techniques, such as "Forwarding Hint", can be also used. In general, "Bolt" is designed on an application level can perform cost estimation, function execution, and states reservation. If users or developers want to run R2 on a computing-capable node such as base stations, gateways, micro data centers and relatively powerful routers, they can simply install the "Bolt" app on the node instead of injecting junk codes or some unexpected behavior into NFD.

# C. R2 Process: A 2-Phase Precise Remote Method Invocation Mechanism

Here, we re-emphasize the kernel question: Given a function with its parameters and the involved metadata, how to select the best node (i.e., the executor) in a distributed manner and obtain the final output result? In other words, how to select an executor in the forwarding path to detect Alice's baby's status.

Before answering this question, three rudimentary points need to be addressed. (1) The requested data should exist, i.e., /alice's-home/remote-monitor-data should exist when Alice wishes to access it, or analysis even by hand is impossible. This point ensures the user a more reliable service. (2) The function cost (for the remainder of the paper, "delay" shall be a substitute for "cost") can be easily estimated. The executor can be quickly chosen based on the function detect and the metadata {resolution:12k, filetype:AVI, size:12MiB}, the executor can be quickly chosen. We use metadata Interest that requests to solve these two points. (3) The executor can be independently, automatically, and distributively selected based on the first and the second point. Some traditional solutions armed with consensus nodes intend to deploy related components or services in the fixed edge nodes (e.g., the edge cloud, which can be regarded as wireless base stations) placed at the level of the network backbone may not be an optimum choice. These solutions fulfill the user's tasks by gathering changeable information but may be trapped in the consensus problem, as the changeable information is not easy to synchronize. The third point refers to selecting the executor based on metadata without requiring additional coordination among nodes or a coordinator and that the metadata is only the information carrier.

Thus, we design the R2 protocol comprising a 2-phase architecture. The first phase neglects those 3 points by selecting the executor through cost estimation based on the function and the retrieved metadata. Developers or maintainers can also start to warm the runtime environment in this phase. The second phase involves executing the function on the executor based on the retrieved Data and then replying the result to the client. Thus, two Interest types are designed, the metadata-Interest and result-Interest, respectively.



Fig. 4. R2 end-to-end delay model.

Technically, compared to metadata-Interest, the result-Interest carries a MinCostMarker<sup>3</sup> used to identify the executor.

The result-Interest might also be sent from a node within the continuum, except for Alice, which we denote as b (bound) for short. An optimized version of R2 in a step-by-step approach is presented in Section III-C.4, illustrated in Fig. 6 (right part), introducing a 2-phase process with its time slices. It should be noted that this version can automatically select the executor with minimal cost by jointly considering the network condition, the data source, and the computation capacity. Next, we introduce in detail the R2 process, including the objective function of minimizing the end-to-end delay, algorithms, and proofs. Then we give a fundamental applied analysis of R2.

1) Modeling the Cost and Selecting the Executor: Objective function. Let  $V = \{v_1, \ldots, v_N\}$  denote a sequence of edge nodes along the path from the client c to the producer p,  $v_i$  is the chosen *i*th node to execute the function,  $C_d^i$  be the computation delay on  $v_i$ , and  $T_{type}^{i,j}$  be the delay of transmitting the *type*-packet from  $v_i$  onto  $v_j$ . Fig. 4 depicts the delay model of R2 and includes the executor selection delays (or the cost estimation, the first phase) and the result processing (the second phase). The first phase mainly selects the best executor  $v_i$  according to the metadata retrieved by sending an metadata-Interest. The second phase retrieves the raw data from p by sending an result-Interest on a node b,<sup>4</sup> performs the function on the node  $v_i$ , and returns the result. Then the end-to-end delay D may be written as:

$$D = \underbrace{T_{metadata-interest}^{c,p} + T_{metadata}^{p,b}}_{\text{cost estimation delay}} + T_{result-interest}^{b,p} + T_{data}^{p,i} + C_d^i + T_{result}^{i,c}$$
(1)

where  $T_{metadata-interest}^{c,p}$ ,  $T_{metadata}^{p,b}$ ,  $T_{result-interest}^{p,i}$ ,  $T_{data}^{p,i}$ , and  $T_{result}^{i,c}$  are the transfer delay of metadata-Interest, metadata, result-Interest, Data, and result, respectively. Formula 1 indicates that the end-to-end delay contains two parts.  $T_{metadata-interest}^{c,p} + T_{metadata}^{p,b}$  is the delay of the executor selection of the first phase, and  $T_{result-interest}^{b,p} + T_{data}^{p,i} + C_d^i + T_{result}^{i,c}$  the result processing delay of the second phase.

<sup>&</sup>lt;sup>3</sup>MinCostMarker tag can be found on https://git.io/J3ysv

 $<sup>^{4}</sup>$ We temporarily use c and b interchangeably. Section III-C.2 gives the specific usage of b.

To minimize the end-to-end delay D, we select the best executor  $v_i$ . Thus, our objective function is  $\min_{v_i \in V} D$ . The cost  $T_{metadata-interest}^{c,p}$  of forwarding the metadata-Interest to the producer is inevitable. Thus, we further simplify the objective function to:

$$\min_{v_i \in V} D$$

$$\Rightarrow \min_{v_i \in V} \{ T^{p,b}_{metadata} + T^{b,p}_{result-interest} + T^{p,i}_{data} + C^i_d + T^{i,c}_{result} \}$$
(2)

 $T_{data}^{p,i}, C_d^i$  and  $T_{result}^{i,c}$  are dominated by the position of executor  $v_i$  within the continuum, where  $v_i$  is the pivot that contributes to D.

We aim to determine  $v_i$  to minimize D. A traditional method checks all the nodes in V by estimating the transmission and computation cost in the first phase. Thus, we write OptimizationOff (OptOff for short), OptOff is a base version of R2 when b = c, i.e., OptOff is a fully two round-trip method. During the first phase (executor selection), it scans all forwarding nodes.

**Cost estimation model.** To determine  $v_i$ , we use a simple cost estimation model that utilizes instant bandwidth of the forwarding path and CPU cycles of the executor. Let a function f have a time complexity  $\mathcal{O}(\cdot)$  and involve a metadata packet M. In R2, the critical indicators in M are typically datasize, metasize of the data and the metadata packet, respectively. Let  $Te_d^{p,i}$  denote the estimated transmitting data delay from p to  $v_i$ , and  $Ce_d^i$  the estimated delay of executing f on  $v_i$ . Then,

$$Te_d^{p,i} = M_{datasize} * \frac{M_{metasize}}{(T_{start} - T_{current})}$$
(3)

and

$$Ce_d^i = \frac{c \cdot \mathcal{O}(M_{datasize})}{CPU_{frequency}} \tag{4}$$

where  $M_{datasize}$ ,  $M_{metasize}$ , c, and  $CPU_{frequency}$  are the size of the original dataset, size of M, CPU cycles per operation, and CPU cycles per second, respectively.

Note that we estimate  $Te_d^{p,i}$  in real-time, and thus, other methods can also be used, e.g., based on historical network interfaces dataset.

Algorithm 1 depicts the executor selection steps in the first phase and from a single node perspective. The algorithm distributively finds an executor and uses a MinCostMarker stored in the metadata to identify the executor  $v_i$ . When the metadata carried a MinCostMarker reaches a client, the Bolt app running on the client extracts the MinCostMarker and attaches it to the result-Interest. This marker is the key to finding the executor in the second phase, and we preserve this marker until the function is executed on  $v_i$ .

However, we argue that finding the executor  $v_i$  in the second half of the first phase does not require traveling all nodes in the path, i.e.,  $v_i \in \{a \text{ subset of } V\}$ . In other words, b can be the node along the path from c to p. Next, we propose an optimization called the *stop condition*.

Algorithm 1 OptOff–Executor Selection (Finding  $v_i$ )

1: if metadata Data packet then

2:  $etaCost \leftarrow costEstimation(metadata); \triangleright Te_d^{p,i} + Ce_d^i$ 

3:  $minCost \leftarrow getMinCost(metadata);$ 

- 4: **if**  $etaCost \leq minCost$  **then**
- 5:  $minCost \leftarrow etaCost;$
- 6:  $MinCostMarker \leftarrow hash(metadata, node.uuid);$ 7: updateMinCost(metadata, minCost,
- 7: updateMinCost(metadata, ma MinCostMarker);



if



Fig. 5. Example of finding the stop point *b*.

2) Stop Condition: In the secretary problem [30], "a manager sequentially observes applicants randomly for a single position. When she observes the b-th applicant in the sequence, she learns only the quality of that applicant concerning those previously seen. Her objective is to select the one who is the best overall—i.e., relative to all applicants, among those seen and those not-yet-seen.". For the scope of this paper, we redefine this problem as **precisely and not probabilistically finding within the continuum the stop point (the bound** b) **without traveling all nodes in** V.

Based on our findings, cost modeling delays  $(T_{metadata}^{p,c/b} + T_{result-interest}^{c/b,p})$  related to finding the best executor in the OptOff method can be further reduced by replacing the "Alice" node c with a strict boundary intermediate node b. Fig. 5 intuitively depicts an example of finding bound b that initiates the result-Interest. This figure presents seven nodes where a computational task with its data is transferred from  $n_1$  to  $n_7$ , and  $n_4$  and  $n_5$  are the most potent backbone nodes or servers. The solid red line shows the computing power of each node. The solid blue line shows the Data transmission delay, and the solid green line shows the total delay. When the transmission delay  $T_{data}^{p,i}$  is greater than the total delay on every passed-by node,  $v_i$  (in this example,  $n_3$ ) is already involved. If we continuously check the remaining nodes after

 $n_5$ , i.e.,  $n_6$  and  $n_7$ , we obtain only the dominated transmission delay. This phenomenon applies to two terminals across the backbone network, such as the cross-edge analytic area [27]. Thus, by replacing the marks in the estimation process, formula 5 gives the *stop condition*:

$$Te_d^{p,b} \ge \max_{1 \le j < b} \left( Te_d^{p,j} + Ce_d^j \right) \tag{5}$$

*Proof:* The stop condition refers to the minimal cost node  $n_m$  is between  $n_1$  and  $n_b$ , i.e.,  $1 \le m \le b$ . The proof's core concept is to consider m', with  $m' \ge b$ , to check if its total cost is smaller than node m. Note that the relation of " $\ge$ " in the stop condition does not change.

Suppose, contrary to our claim, that the stop condition is false. Then we could find an  $m' \geq b$  and  $Te_d^{p,m'} \geq Te_d^{p,b}$ , imposing a minimal cost of  $Te_d^{p,m'} + Ce_d^{m'}$ . Then,

$$Te_d^{p,m'} + Ce_d^{m'} \le \max_{1 \le j < b} (Te_d^{p,j} + Ce_d^j)$$

Because  $Te_d^{p,m'} \ge Te_d^{p,b}$ , thus

$$Te_d^{p,m'} + Ce_d^{m'} > Te_d^{p,b}$$

Finally, we get

$$\max_{1 \le j < b} \left( Te_d^{p,j} + vCe_d^j \right) < Te_d^{p,m'} + Ce_d^{m'} \le \max_{1 \le j < b} \left( Te_d^{p,j} + Ce_d^j \right)$$

Hence, m' = j < b, contradicting our assumption that m' > b. When this condition is met, we stop the executor selection process.

Based on the stop condition, Algorithm 2 presents an optimized version of Algorithm 1, termed OptimizationAuto (OptAuto for short).

Algorithm	2 OptAuto-	-Executor	Selection	(Finding	$v_i)$	Within
Bound b						

1: procedures of Algorithm 1;

2: if metadata Data packet then

3:  $maxCost \leftarrow getMaxCost(metadata);$ 

4: **if**  $Te_d^{p,i} \ge maxCost$  **then**  $\triangleright$  the stop condition 5: TURN INTO second phase;  $\triangleright b$  is found

- 6: else if maxCost < costEta then
- 7: updateMaxCost(*metadata*, *maxCost*);

8: **end if** 

9: end if

3) Applied Range Analysis of R2: Analyzing the stop condition. The stop condition can operate automatically as a plugin. This subsection gives a simple applied range analysis, especially for the edge where the network and computing are resource-constrained. It should be noted that  $n_j$  is the slowest node executing the function within the continuum. Thus, we leave out the max symbol, i.e.,  $Te_d^{p,b} \ge Te_d^{p,j} + Ce_d^j$ .

The analysis comprises two scenes, a store and forward network (e.g., NDN) and a universal network (e.g., NDN, TCP/IP).

(1) Store and forward network:

$$\begin{split} Te^{p,b}_d \geq Te^{p,j}_d + Ce^j_d & \Longrightarrow \quad Te^{p,b}_d - Te^{p,j}_d \geq Ce^j_d \\ & \stackrel{sn}{\Longrightarrow} \quad Te^{j,b}_d \geq Ce^j_d \end{split}$$

where sn represents for a store and forward network.  $Te_d^{j,b} \ge Ce_d^j$  indicates that the stop condition operates with the scene where the computational throughput, i.e.,  $datasize/Ce_d^j$ , of the slowest node  $n_j$  exceeds the transmission throughput from  $n_j$  to  $n_b$ . Here, b is the terminal (e.g., the client).

(2) A universal network:

$$Te_d^{p,b} \ge Te_d^{p,b} - Te_d^{p,j} \implies Te_d^{p,b} \ge Ce_d^j$$

We eliminate the transmission delay from p to  $n_j$  (i.e.,  $Te_d^{p,j}$ ) in the universal network, which is a relatively tight constraint.  $Te_d^{p,b} \geq Ce_d^j$  indicates that the stop condition operates with the scene where the computational throughput of the slowest node  $n_i$  exceeds the transmission throughput from p to  $n_b$  (or the terminal). This is useful when the delay in transmitting data from  $n_i$  to  $n_b$  is challenging to estimate. R2 vs. 1-round or 1-phase methods. It should be emphasized that R2 has the benefits presented at the beginning of Section III-C, even if the total delay is bigger than the 1-round methods in some cases. Nevertheless, if the raw data is limited or the function is simple, R2 may not outperform the 1-round methods (the methods regarding the Client or Producer as the executor). Hence, we compare R2 and Client in NDN to examine the applicability of R2 in terms of the total delay. Without a loss of generality by assuming b = c, R2 involves fully 2-phase operations in the worst case.

$$\begin{split} T^{c,p}_{interest} + T^{p,c}_{data} + C^c_d &> D \\ \implies T^{p,c}_{data} + C^c_d > T^{p,c}_{metadata} + T^{c,p}_{result-interest} \\ &+ T^{p,i}_{data} + C^i_d + T^{i,c}_{result} \end{split}$$

Because the metadata contains limited information, the metadata size can be roughly equal to the result-Interest. Then, by

$$T_{metadata}^{p,c} + T_{result-interest}^{c,p} \approx 2 \ T_{interest}^{c,p}$$

We obtain

$$\implies T_{data}^{p,c} + C_d^c > 2 T_{interest}^{c,p} + T_{data}^{p,i} + C_d^i + T_{result}^{i,c}$$

$$\implies T_{data}^{p,c} - T_{data}^{p,i} - T_{result}^{i,c} > 2 T_{interest}^{c,p} + C_d^i - C_d^c$$

$$\implies T_{data}^{i,c} - T_{result}^{i,c} > 2 T_{interest}^{c,p} + C_d^i - C_d^c$$

It is clear that the computing power of  $n_i$  is bigger than c, and thus  $C_d^i < C_d^c$ . Writing  $\delta = C_d^c - C_d^i$ , then

$$\implies T_{data}^{i,c} - T_{result}^{i,c} > 2 \ T_{interest}^{c,p} - \delta$$

Let  $\alpha$  be the ratio of the output *result* size to the input *data* size.

$$\implies (1-\alpha)T_{data}^{i,c} > 2 T_{interest}^{c,p} - \delta$$

In most data-intensive functions or applications,  $\alpha \ll 1.$  Then,

$$\stackrel{\sim}{\implies} T^{i,c}_{data} > 2 \ T^{c,p}_{interest} - \delta$$

From the latter equation, we observe that if  $2T_{interest}^{c,p} < \delta$ , i.e., the client's computing power is smaller than node *i* within the

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continuum, and the data size is greater than the result. This applied condition is always true. Second, if the computing resources are similar within the continuum, then  $\delta \approx 0$ . For the data size analysis, we obtain

$$T_{data}^{i,c} - T_{result}^{i,c} > 2 T_{interest}^{c,p} - \delta \xrightarrow{\sim} T_{data}^{i,c} > 2 T_{interest}^{c,p} + T_{result}^{i,c}$$
(6)

Inequality 6 means the data size should be at least greater than the 3-folds of the interest when i is in the vicinity of p, which is trivial.

4) R2 Process in a Step-by-Step Approach: Fig. 6 presents OptAuto by depicting two phases (comprising five processes or steps) of the R2 protocol under Alice's example, who wants to check her baby's status. By neglecting the stop condition, R2 becomes a fully 2-phase process. Due to the page size, we involve four computing-capable nodes  $(n_1, \ldots, n_4)$  and one forwarding node  $(n_5)$ . The left area in Fig. 6 provides the R2 steps from the node perspective, while the right area gives a bird's eye view of the time delays per step. In Alice's example, she first sends a metadata Interest to get the remotemonitor-data abstract. R2 automatically creates the traceable traces, finds the best executor of "detect", retrieves raw data of remote-monitor-data, analyzes her baby's status, and finally sends the baby's status to Alice. We describe these five steps in detail below.

(1) Alice first sends a long-lived metadata-Interest (under the name /r2/alice's-home/remote-moni tor-data/sep/ detect/{object=baby, action= position}) into NDN. This Interest passes through the nodes within the continuum, is captured by Bolt, leaves a mapping correspondence in ITT, and finally reaches the producer (or the camera at Alice's home). The time consumed  $T_{metadata-Interest}^{c,p}$  in this process is positively correlated with the packet size of the metadata-Interest and the number of hops between Alice and her home.

(2) The producer first replies with a metadata Data packet containing {resolution:12k, filetype:AVI, size:120MiB}. When the metadata moves towards Alice, two critical actions are performed. The first is to find the executor with a minimal end-to-end delay cost D based on node configuration, "detect", and metadata. According to the stop condition, the second is to find the boundary b, i.e.,  $n_3$ . R2 discards the created mapping correspondence (red records) to reduce the ITT size in this process. After this process, we obtain a MinCostMarker representing the executor, i.e.,  $n_4$ . This marker comprises "detect", parameters and the node's UUID, which can be viewed as the identifier of Alice's request. The time consumed  $T^{p,b}_{metadata}$  in this process is positively correlated with the packet size of metadata and the cost estimation step, which is insignificant.

(3) b issues a result-Interest carrying the MinCostMarker to the producer. Since all we need is the raw data, i.e., the HD video file remote-monitor-data, any other operations during transmitting the raw data between b and the producer are needless. Thus, the result-Interest of the newly added mapping correspondence in ITT (green records) is set to be the Non-Long-Lived Interest type. We can also perform warm-up services, e.g., video/image data processing unit, DNN model, and libraries related to performing detect(baby, position), on  $n_4$  when it receives the notification from b to avoid a cold start. The time consumed  $T_{result-Interest}^{b,p}$  in this process is positively correlated with the packet size of result-Interest, the number of hops between the boundary and Alice's home. For completeness, it should be mentioned that the path guided by the NDN routing table (or PIT), despite being unstable, it can be settled through session support [29].

For the step (4) and (5), the executor (i.e.,  $n_4$ ) runs the function after it receives the Data to provide Alice's baby's status. Finally, the result is returned to the client. The time consumed in processes 4 and 5 comprise and are positively correlated with three parts: result transfer delay  $T_{result}^{i,c}$ , computation delay  $C_d^i$  and raw data transfer delay  $T_{data}^{p,i}$ .

#### IV. EVALUATION AND RESULTS

To evaluate R2's performance, we design an intermediate data processing logic on the "Bolt" application level and implement it in ndnSIM. This section first illustrates the "Bolt" logic (Section IV-A) and then exploits it to evaluate R2 (Section IV-B).

#### A. R2 Bolt: Intermediate Data Processing on App Level

Automatically running a function requires a modular implementation not only for maintenance but also for development. A general forwarding framework named NDN-trace [31] processes the intermediate Interest and Data. From a scalability and compatibility perspective, we extend NDN-trace and perform a custom forwarding strategy to support function execution on an application level, i.e., Bolt.<sup>5</sup> Next, we provide the R2 Bolt app details.

Fig. 7 depicts the custom forwarding strategy pipeline of R2. The red and green dotted lines frame the R2 Strategy and the NFD (the NDN Forwarding Daemon). When NFD receives an R2 Interest, it is forwarded according to the FIB (Forwarding Information Base) to the Bolt of that node. Inside NFD, R2 Interests are handed over to our custom R2 Strategy extended from the native BestRouteStrategy2 of NDN. R2 Strategy first performs a next-hop lookup on the actual data name /alice's-home/remote-monitor-data only, extracted by the "get lookup name" method instead of the entire R2 Interest name with the prefix "/r2". Then, after checking the FIB, we directly obtain the next hop (or face) matched to the name /alice's-home/ remote-monitor-data by performing the method "get next hops". At last, /r2/alice's-home/ remote-monitor-data is directly sent to the matched next hop (or face). Note that the next hop (or face) contains two types: Bolt and the next hop node. Because the Bolt app registers the prefix "/r2" using InterestFilter, it can directly identify and capture

<sup>&</sup>lt;sup>5</sup>The name "Bolt" is inspired by Apache Storm. In Apache Storm, the logic for processing data tuples in a node is called a "Bolt".



R2 process in a step-by-step approach: an auto-mode to select executor.

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Fig. 7. R2 forwarding strategy.



Fig. 8. Forwarding interest/data using Bolt app.

the R2 Interest. If the node does not install the Bolt or is a computing-incapable node R2 Strategy, it will forward /r2/alice's-home/remote-monitor-data to the direction of /alice's-home/remote-monitor-data directly. The entire process is repeated at every node encountered on the path(s) until R2 Interest /alice's-home/remote-monitor-data reaches the target prefix, i.e., Alice's home.

Fig. 8 depicts a forwarding pipeline using three computingcapable nodes to demonstrate the Bolt logic. To simplify the process, we do not distinguish between Metadata and Data. Alice  $(n_1)$  sends an Interest (under the name /r2/alice'shome/remote-monitor-data/sep/detect/paras) into the upstream. Its true data name /alice's-home/ remote-monitor-data is first extracted by a custom Strategy implemented at the NFD level, and then it is forwarded to the next hops according to the forwarding policy by scanning FIB.<sup>6</sup> When the incoming R2 Interest is received by the NFD, which has Bolt installed, it is caught by Bolt Face and transmitted into the processing logic (processingInterest in Fig. 9). Currently, Bolt has an Interest Trace Table (ITT) performing three actions: (1) Clones the incoming Interest and append a random number

 $^{6}$ It is worth noting that R2 Interest starts with a prefix /r2 (Fig. 3), while the forwarding process of NFD only cares about /alice's-home/remote-monitor-data. Thus, the right sub-components in the names are extracted through custom Strategy in the NFD level to enter the proper forwarding pipeline. The Interest Name in PIT is still starts with /r2 and does not change.

```
void onInterest(const InterestFilter& filter, const
Interest& inInterest)
{
    // Discard looped Interest
    if (Islooped(inInterest)) return;
    // Clone the incoming Interest and create the
    mapping relationship
    preProcessingInterest(inInterest, outInterest);
    // Process the cloned Interest (i.e., outInterest);
    processingInterest(filter, inInterest, outInterest);
    // Issues the cloned Interest
    afterProcessingInterest(inInterest, outInterest);
}
```

Fig. 9. Pseudo-code of processing an incoming Interest in Bolt: a single node perspective.

(Interest identifier, e.g., 11, 12,....) to the tail of the cloned Interest Names. (2) Creates a mapping entry between the cloned and the origin Interest and inserts the entry into ITT. (3) Deletes the entry if the Interest is satisfied (red records in ITT). Additionally, since the function execution process may take time, another important role of ITT is manipulating the lifetime (Long-Lived Interest flag in ITT) of the R2 Interest to avoid the time-out issue imposed by solely employing PIT. As the ndnSIM declares, these codes can be applied to the production with minor modifications.

The pseudo-code to process an incoming Interest is depicted in Fig. 9. The parameter inInterest can be referred to as I1, I2, and I3 (start with a prefix /r2) that flows into Bolt in Fig. 8. Line 6 first clones those incoming Interests then inserts the mapping relationship into ITT,



Fig. 10. Rocketfuel dataset.

and finally exits the cloned outInterest. Sending out the outInterest (Line 10) refers to I2, I3 and I4 that exit Bolt in Fig. 8. In the processingInterest (Line 8), some additional operations can be applied to outInterest, e.g., make the interest long-lived, or add user-interested tags. In the R2 Bolt, processing the Data is technically the same as processing Interest logic. For further details, the reader is referred to the source code.<sup>7</sup>

## B. Evaluation

This section evaluates R2 via an extensive simulation study. We implement four notable methods, including OptOff and OptAuto, to testify the end-to-end delay in ndnSIM [18], where ndnSIM is an NS-3-based simulator for NDN [13] implementation. Two additional methods are the "Producer" and "Local", where the former means pushing the function down to the storage (data location), a typically distributed database management method. However, the Producer's computing power and energy are usually limited. The Local method considers the client directly retrieving the Data and executing the function itself. All R2 codes are based on ndnSIM-2.8, NFD-0.7.0, and all the experiments are performed on macOS utilizing an Intel i5 Dual-core at 2.7GHz.

**Dataset.** We adopt a real-world network topology, i.e., rocketfuel [32], comprising 282 nodes, including 177 clients, 89 gateways, and 16 backbones. The topology is illustrated in Fig. 10, where the two yellow nodes are the client (c) and the producer (p). The blue backbone is the high-level performance edge node, the green gateway is the middle-level performance edge node, and the red device is the low-level edge node performance. Table II shows this topology's configurations, where H and M denote the high and middle performance, respectively, and C the end device (Client or Producer). It is worth noting that the available bandwidth is the total bandwidth split by numerous nodes due to concurrency and collision.

**Indicators.** We focus on measuring the average end-toend delay and the hop-by-hop delay. End-to-end delay is used to compare four methods, and the hop-by-hop delay is used to test whether the stop condition is working. Different complexity of the function can have a different impact on the

TABLE II TOPOLOGY CONFIGURATION

Item	H(-H)	H(-M)	M(-C)
Available bandwidth (Mbps)	$10 \sim 40$	$20\sim40$	$40 \sim 100$
CPU (GHz)	$3 \sim 4$	$2\sim 3$	$0.5\sim 2$
Memory (GB)	$32 \sim 128$	$8\sim 32$	$2\sim 8$



Fig. 11. End-to-end delay of 4 methods.

cost estimation model. Thus, given the competitor methods, we categorize the time complexity of the function as  $\mathcal{O}(logn)$ ,  $\mathcal{O}(n)$ , and  $\mathcal{O}(n^2)$  and fixed space complexity as  $\mathcal{O}(n)$ ,<sup>8</sup> where n is the data size. In the simulation, we set the ratio of the function output size to its input data size as  $\alpha = 0.1$ .

## C. Results

Fig. 11 presents the end-to-end delay of the four evaluated methods by varying the data size and time complexity. Fig. 9 indicates that the end-to-end delay increases as the data size and complexity rise. When the data size is small, i.e., data size < 102 bytes, both the Local and Producer present a low delay level. However, when the data size exceeds 1024 bytes (1 KiB, which is very rare in today's network communication), OptAuto and OptOff gradually get better than the Local and Producer. Hence, the executor is essential for the computations within the continuum.

Fig. 11 (a) illustrates that OptOff, which has a complexity of  $\mathcal{O}(logn)$ , is always at a high level because it needs a fully two-round-trip to find the executor and the transmission dominating the total delay. Since the  $\mathcal{O}(logn)$  operations are not large, the Producer is faster than the competitor methods. Nevertheless, we do not prefer the task compute at the producer because its computing power is usually limited. Meanwhile, OptAuto obtains a similar result with the Producer when the data size is larger than 1024 bytes, i.e., the bound

<sup>8</sup>For further information on IOPS the reader is referred to: https://docs. aws.amazon.com/AWSEC2/latest/UserGuide/ebs-io-characteristics.html

<sup>&</sup>lt;sup>7</sup>Intermediate data processing code in Bolt: https://git.io/J3iux



Packet flow type - Data - Inter



(c) Hop-by-hop accumulating delay of  $\mathcal{O}(n^2)$ .

Fig. 12. Hop-by-hop accumulating delay of OptAuto and OptOff varying data size.

b is found, and a fully two-round-trip compared with OptOff is avoided. Local also presents an increased processing time once the data size exceeds 1024 bytes, which integrating with OptAuto implies that the computation and the transmission delays are of the same order and both dominate the total delay. It should be noted that the methods having  $\mathcal{O}(logn)$  complexity are not everywhere reachable, especially in the data analysis realm. Fig. 11 (b) and Fig. 11 (c) the four methods with  $\mathcal{O}(n)$  and  $\mathcal{O}(n^2)$ , respectively. From this figure, it is evident that OptAuto manages an acceptable result compared with Local and Producer. When the data size reaches 100 KiB, the speedup ratio Local/OptAuto reaches 1.84, 2.37, and 4.61 for  $\mathcal{O}(logn)$ ,  $\mathcal{O}(n)$ , and  $\mathcal{O}(n^2)$ , respectively.

From the stop condition analysis of Section III-C.2, we know that the bound b is related to the time complexity and transmission delay. Next, to verify whether the bound b is found, we plot the hop-by-hop accumulating delay of OptAuto and OptOff varying data size (entitled "Method-Datasize"), presented in Fig. 12. It is straightforward that in most cases, OptAuto finds the bound b compared to the OptOff in most cases, OptAuto finds the bound b compared to the OptOff. Most importantly, OptAuto gives the same executor as OptOff, proving the effectiveness of the stop condition that does not check all nodes.

## V. DISCUSSION

The reader might have security-related concerns for the Interest and Data intermediate processing. However, this is a well-discussed topic in [13] and [31]. In addition to ICN's content-based security model, we implement our solution on an application and not system level, and thus many possible ways can be utilized to enable authentication services. Feasible solutions involve nodes within the continuum having the public key of each other or other decentralized authentication methods [33]. Nevertheless, security concerns are out of this paper's scope, and thus we will not further examine them.

This version of R2 focuses on how to pick the best computing-capable executor within the forwarding path. Thus, mobility is not paid much attention. Recent mobility-related works mainly focus on two types of nodes (consumer and producer) and three categories (mapping-based, tracing-based, and data depot) [34], [35], [36]. For R2, mobility support needs to be built on top of these ideas. Specifically, in R2, the executor is the role of the consumer compared to the data producer, and the role of the data producer remains unchanged. Thus, if the producer moves, the methods mentioned in [34], [35], and [36] can be adapted. Another problem is that intermediate forwarding nodes have mobility. Current works have not paid much attention to the intermediate forwarding nodes, but it is more common in self-organizing and stochastic networks. For the consumer, the executor is the role of the producer that may use a tracing-based approach to proactively inform the nodes on the forwarding path to establishing a new channel, which ensures that the executor is always accessible. Another solution is to carry the unique identifier of the executor as a hint when the executor performs the process of returning ACK Data to the consumer, which ensures that we can eventually look up the executor.

# VI. CONCLUSION

This paper discusses the feasibility of R2, a 2-phase novel mechanism for data processing in edge computing. A 2-phase

design has many potential benefits, ensuring the function execution integrity, checking the node's health status in the client's path towards the producer, and, most importantly, choosing the best node to execute the function. R2 leverages the NDN paradigm for data retrieval from data sources, enhances it to provide a decentralized method invocation mechanism with the objectives to (1) minimize the endto-end delay by limiting the raw data traffic crossing the network and selecting the executor and (2) reduce the first round trip time by an intelligent stop condition. In addition, we developed "Bolt" to process the intermediate data on the app level in ndnSIM. "Bolt" can be installed on the selected computing-capable nodes to provide scalable service. We believe that our freely available code [19] can help researchers and developers verify their ideas smoothly.

## VII. FUTURE WORKS

Currently, R2 only handled a single user request in this paper. We solve the multi-user requests, including "compute reuse" in the future. Future works also include extending R2 to handle application (i.e., solving the functions/tasks directed acyclic graph (DAG)), re-forwarding the user's Interest according to function name by the intermediate nodes to scale out the executor selection space, storing metadata and data with different locations.

Changing metadata-Interest's lifetime from long-lived to regular is another future work. We think the latter is feasible and is currently implemented by inflating the timer of the metadata-Interest entry in the PIT through sending a refreshing Interest or an ACK Data that carries the estimated function-execution time from the selected executor back to the consumer. This is similar to RICE's "Interest Acknowledgements" [16]. The most significant difference is that the refreshing action in R2 is sent from the executor and not from the consumer or the producer. Because the executor has the metadata, R2 affords a more precise function-execution time.

Instead of identifying and capturing the current R2 Interest by the prefix "/r2", effectively capturing the Interests at the application level by identifying the user-selected Name components is another future research direction. Note that our purpose is still putting the computation logic on the application level, not the NFD level. Another possible solution is adding "/r2" as a postfix, identifying the postfix "/r2" and forwarding it to the face of the Bolt app instead of the next-hop node, which still integrates with the forwarding Strategy. This Strategy seems similar to the Interests tracing method KITE [36] and opposes the current R2 Strategy. To the best of our knowledge, designing a scalable naming convention is a concern of many recent works that put the function or service identifier at the head of the Name, e.g., name as a function. Overcoming this issue may bring R2 scalability into a new stage.

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**Jianpeng Qi** received the B.S. and M.S. degrees in computer software and theory from Yantai University, Yantai, China, in 2015 and 2018, respectively. He is currently pursuing the Ph.D. degree in computer science and technology with the University of Science and Technology Beijing under the supervision Prof. R. Wang. His research interests include resource management, reliability, and edge intelligence.



**Rui Wang** (Member, IEEE) received the Ph.D. degree in pattern recognition and intelligent systems from Northwestern Polytechnical University, Xi'an, China, in 2007. He is currently a Professor with the Department of Computer Science and Technology, School of Computer and Communication Engineering, University of Science and Technology Beijing, China. His research interests include edge intelligence, mobile and ubiquitous computing, and distributed systems.