Content Delivery Latency of Caching Strategies for Information-Centric IoT

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Abstract—In-network caching is a central aspect of Information-Centric Networking (ICN). It enables the rapid distribution of content across the network, alleviating strain on content producers and reducing content delivery latencies. ICN has emerged as a promising candidate for use in the Internet of Things (IoT). However, IoT devices operate under severe constraints, most notably limited memory. This means that nodes cannot indiscriminately cache all content; instead, there is a need for a caching strategy that decides what content to cache. Furthermore, many applications in the IoT space are time-sensitive; therefore, finding a caching strategy that minimises the latency between content request and delivery is desirable. In this paper, we evaluate a number of ICN caching strategies in regards to latency and hop count reduction using IoT devices in a physical testbed. We find that the topology of the network, and thus the routing algorithm used to generate forwarding information, has a significant impact on the performance of a given caching strategy. To the best of our knowledge, this is the first study that focuses on latency effects in ICN-IoT caching while using real IoT hardware, and the first to explicitly discuss the link between routing algorithm, network topology, and caching effects.

Index Terms—Information-Centric Networking, Named Data Networking, Internet of Things, In-Network Caching, Network Topology.

I. INTRODUCTION

The content-centric nature and slim network stack of Information-Centric Networking (ICN) make it an ideal candidate for a future network architecture for Internet of Things (IoT) applications [1]–[5]. However, the fact that resources such as memory, processing power, and battery life are traditionally severely limited in the IoT means that the automatic and indiscriminate caching of all content in the network, as is common in traditional ICN, can not be transferred to this domain. Memory in particular is a much more valuable resource in IoT applications, so approaches that simply assume that all content will be cached at all nodes are not feasible. Instead, the questions of what content should be cached, which nodes should cache it, and for how long it should be cached become central questions of ICN-IoT in-network caching. Although these questions have been explored in traditional ICN research, a large number of potential solutions still assume cache sizes that are unrealistic in IoT environments, and their application to IoT-specific deployments has proven sub-optimal [6]–[10]. It is therefore desirable to find caching solutions that are especially geared towards addressing the constraints unique to the IoT.

Apart from increasing content redundancy and decreasing network load, efficient in-network caching can also reduce content delivery latencies by making content more readily available across the network [11]. Operating under the assumption that content, once produced, will remain useful for a certain amount of time and will be requested by multiple consumers during its lifetime, an effective caching strategy will minimise the distance between consumers and cached copies of the content they require. Given an information-centric IoT application where a reduction in content delivery latency is the primary objective, we want to compare and contrast the effect different approaches to ICN in-network caching have on this metric.

The question of where in the network content should be cached is one of the most defining problems of in-network caching research [12]–[15]. In particular, it has not been definitively established whether it is better to cache content towards the edge of the network (i.e. closer to the consumer) or towards the core, i.e. closer to the producer. Intuitively, caching closer to the consumer would seem to make more sense; after all, if we keep content close to the producer, we can reduce the load on that particular node, but the potential latency improvements seem to be minimal. If content is requested from a particular region of the network, it is probably safe to assume that it will be requested from that region again in the future. If the content was already cached close to that region, retrieving it will be much faster. This is the argument for caching towards the consumer and there are a number of caching strategies that employ this paradigm [13], [16]–[18]. However, as we will show in Section III-C, depending on topology, there is also a strong argument for the inverse approach.

In this study, we will be evaluating a number of different in-network caching strategies. To achieve this, we design an experiment using real IoT hardware in a physical testbed meant to emulate the conditions of a typical IoT application as closely as possible. We measure content delivery latencies as well as the average reduction in hop count between cached content and original storage location. We also investigate the extent to which the effectiveness of a given strategy is influenced by the network topology and thus the routing algorithm.

Although other authors have investigated and compared...
ICN-IoT caching strategies using various performance metrics (see Section IV), there has not been an in-depth study exclusively focused on latency effects, and none of the existing studies have used physical IoT hardware to perform their experiments. Furthermore, no existing studies explicitly take the strong correlation between routing algorithm, network topology, and caching effects into account. These are the key contributions of this paper.

This paper is structured as follows:
- We introduce a number of modern caching strategies for ICN and discuss their suitability for the IoT (Section II).
- We evaluate and compare the caching strategies introduced in Section II in regards to metrics such as hop count and latency reduction (Section III). We also discuss the effects of network topology.
- We discuss related research in the field of caching in ICN with a focus on IoT (Section IV)
- Finally, we present potential future research directions (Section V).

II. CACHING STRATEGIES

The original Content-Centric Networking (CCN) proposal [19] did not place a strong focus on caching policies. It was assumed that nodes would simply cache all received content indiscriminately. It has since been shown [12], [13], [20], [21] that caches can be utilised more effectively using more advanced caching policies.

In this section, we will introduce different approaches to caching policy with varying complexity. For every strategy that we evaluate in Section III, we will provide a pseudocode definition here. Every strategy provides two functions, HANDLE_INTEREST() and HANDLE_DATA(), which define what the strategy does upon reception of an Interest or Data packet, respectively. There are also functions that are not further defined in the pseudocode, such as canSatisfy(), which returns true if the incoming Interest can be satisfied locally and false otherwise; getData(), which retrieves a content chunk from the local Content Store (CS); and the NDN primitives reply() (for replying to an Interest with a Data packet), forward() (for forwarding Interest and Data packets to the next hop), and cache() (for caching content).

A. Cache Everything Everywhere (CEE)

The simplest approach to the caching decision is for every node to cache every piece of incoming content. This requires no computational overhead and leads to rapid proliferation of content across the network; however, it also results in high cache redundancy and thus suboptimal resource use. It has become consensus [12], [13], [20] that this strategy is not optimal in terms of providing redundant access to as large a subsection of available content as possible; instead, caches tend to hold only the most recent content and the danger of thrashing is high. Depending on the application, however, Cache Everything Everywhere (CEE) (Algorithm 1) can have a positive effect on content delivery latencies, since it is the fastest way to proliferate new content throughout the network; the more content requests are skewed towards recent content, the more they may benefit from CEE.

Algorithm 1 Cache Everything Everywhere (CEE)

```python
1: function HANDLE_INTEREST(Interest)
2:     if canSatisfy(Interest) then
3:         Data ← getData(Interest)
4:         reply(Data)
5:     else
6:         forward(Interest)
7:     end if
8: end function

10: function HANDLE_DATA(Data)
11:     if Data.TSB = 1 then
12:         cache(Data)
13:     end if
14:     Data.TSB ← Data.TSB + 1
15:     forward(Data)
17: end function
```

B. Leave Copy Down (LCD)

If we do not want to cache everything at every node, but also do not want to introduce complex additional steps into the caching process, we can use a policy called Leave Copy Down (LCD) (Algorithm 2). In LCD, content is always cached only at the next hop from the node where the cache hit occurred (i.e. the first node to receive the Data) and nowhere else. We achieve this by extending the Data packet with a Time Since Birth (TSB) field, which counts the number of hops since the creation (“birth”) of the Data packet. TSB is initially 1 and is incremented every time the Data packet is forwarded. Nodes only cache Data with a TSB of exactly 1.

LCD is a somewhat “conservative” caching strategy that tends to keep content close to the producer, but still alleviates load on the producer. Since every cache hit results in the content being cached one hop closer to the requesting consumer, popular content that is requested with high frequency will gradually move the content closer to consumers with each step.

Algorithm 2 Leave Copy Down (LCD)

```python
1: function HANDLE_INTEREST(Interest)
2:     if canSatisfy(Interest) then
3:         Data ← getData(Interest)
4:         Data.TSB ← 1
5:         reply(Data)
6:     else
7:         forward(Interest)
8:     end if
9: end function

11: function HANDLE_DATA(Data)
12:     if Data.TSB = 1 then
13:         cache(Data)
14:     end if
15:     Data.TSB ← Data.TSB + 1
16:     forward(Data)
17: end function
```
C. Probabilistic Caching

The easiest way to achieve higher cache diversity without increasing the complexity of the caching policy is to cache probabilistically. In the static version of this approach, commonly known as $\text{Prob}(p)$ (Algorithm 3), we set a static probability $p$ that governs how likely a given node will cache a given content chunk. It has been shown [6], [22] that $\text{Prob}(p)$ outperforms CEE in terms of cache diversity, and that lower values for $p$ correlate with higher diversity [6], [7], [9], [13], [22], [23].

However, instead of defining an a priori caching probability that is the same for every caching decision at every node, we can also design a technique that dynamically computes a caching probability for each individual node or even for each content chunk, based on available information, in order to adapt the caching behaviour to the state of the network. These strategies could be based purely on node-local information, such as the current contents of the cache or the node’s battery levels; they could also be based on properties of the incoming content chunk, such as its age, type, or producer; or they could be based on information from the wider network, such as the position of the caching node in the network topology or the cache contents of neighbouring nodes.

Psaras et al. propose $\text{ProbCache}$ [13] (Algorithm 4), which computes the caching probability of a given content chunk based on the total number of hops between its producer and the consumer that requested it, as well as the number of hops remaining on the path to the consumer. For a given content chunk travelling a path between producer and consumer, $\text{ProbCache}$ determines the cache weight at each node, which is determined by the Data packet’s TSB (see Section II-B) as well as its Time Since Inception (TSI), which is the number of hops between the creation (“inception”) of the corresponding Interest packet and the cache hit, i.e. the total length of the path between consumer and producer. This means that content chunks are cached with a higher probability towards the edges of the network (i.e., closer to the consumer), adjusted by the length of the Interest packet’s path. The authors find that in traditional ICN, $\text{ProbCache}$ increases the cache hit ratio, reduces the average number of hops required to hit requested content, and reduces the number of cache evictions.

As will be discussed in more detail in Section III-C, depending on network topology, caching closer to the consumer may not necessarily be the most efficient caching policy; in some topologies, caching closer to the producer is more beneficial. $\text{ProbCache}$ is easily modified to take this consideration into account by simply inverting the caching probability such that content is more likely to be cached near the producer. We call this modified strategy $\text{ProbCache-Inv}$ and it is identical to $\text{ProbCache}$ in every way except that the final caching probability is inverted (i.e. line 16 in Algorithm 4 reads if rand() < CacheWeight then).

D. Cooperative Caching

Cooperative caching is an umbrella term for caching strategies that take more than local information into account, i.e., strategies in which nodes either implicitly or explicitly coordinate with their neighbours to ensure optimal caching. In explicit coordination, nodes may exchange information about their cache contents and/or the contents they have received on a periodic or ad hoc basis in order to make caching decisions, or even forward content chunks to one another for caching.

In implicit coordination, nodes follow a priori rules that govern what content they can cache, thus avoiding the need for explicit coordination. One example of this was proposed by Li and Simon [24] (Algorithm 5), where each node is assigned a fixed label $l < k$ at setup and only caches content chunks whose IDs modulo $k$ are equal to $l$. This ensures that cached content is automatically stratified into equal subsets and evenly distributed across the network without the overhead of explicit coordination between nodes. By adjusting $k$, it is possible to control the level of stratification. We will call this caching strategy $\text{Labels}$ for the remainder of this study.
Zeng and Hong [25] (Algorithm 6) propose an implicitly coordinated caching strategy that uses hop distance to determine the caching decision. Data packets are extended by a pre-determined data interval value $i$. Each node along the path decrements this value by 1 when forwarding the packet. If a node decrements its value to 0, the packet is cached at that node and the data interval is reset to $i$. This ensures that data are implicitly cached at regular distances from producers without requiring any topological information or coordination. We will call this caching strategy Intervals for the remainder of this study.

E. Other approaches

In the following, we will briefly cover a number of alternative strategies which we will not be evaluating in this study because their complexity, their overhead, or other factors make them infeasible for use in the IoT.

Algorithm 5 Labels($k$)

| Line | Description |
|------|-------------|
| 1:   | function HANDLE_INTEREST(Interest) |
| 2:   | if canSatisfy(Interest) then |
| 3:   | Data ← getData(Interest) |
| 4:   | reply(Data) |
| 5:   | else |
| 6:   | forward(Interest) |
| 7:   | end if |
| 8:   | end function |
| 9:   | function HANDLE_DATA(Data) |
| 10:  | if Data.ID mod $k = $myLabel then |
| 11:  | cache(Data) |
| 12:  | end if |
| 13:  | forward(Data) |
| 14:  | end function |

Move Copy Down (MCD) is a variant of LCD (Section II-B) in which instead of simply copying a content chunk to the next node whenever a cache hit occurs, that content chunk is explicitly moved to the next node; i.e., it is deleted from the current cache and only stored in the next cache. This would free up cache space for new content near the core. We decided not to investigate this approach because the underlying principle is virtually identical to LCD and there is not much further insight to be gained from studying it.

ProbCache (Section II-C) is representative of a broader family of caching strategies with dynamic probability, which can take a multitude of weighted factors into account when calculating their caching probabilities. Other such approaches may use some combination of node battery level and cache occupancy in their calculations, along with some information about the incoming content, e.g. its freshness [6], [26] or its popularity [27], whether the content is already cached in a neighbouring node [28], and/or topological information such as hop count [26], [28] or the caching node’s centrality [27], [29]. The space of possible permutations of parameters for probabilistic caching is very large, so we decided to focus on ProbCache as the sole representative.

Explicit cache coordination strategies tend to be more complex than their implicit counterparts (Section II-D), requiring more communication among the nodes and more calculations to maintain a consistent state. For example, Liu et al. [30] propose a strategy that coordinates nodes by constructing a virtual backbone network using graph-theoretical concepts to create a node hierarchy with core nodes responsible for caching. However, since one of the primary goals of optimising strategies for use in the IoT should be a minimisation of overhead, we will not be considering any explicit coordination strategies in this comparison.

Vural et al. [31] propose a strategy that uses the popularity of content classes to calculate the cost function for the caching of incoming content. Nodes cache content until it reaches a certain age, and for each incoming content chunk, the caching node calculates how many Interests the chunk can be expected to satisfy during its lifetime. Content that is expected to serve more Interests — because its content is more popular and/or because it is more fresh — is cached with a higher probability. Popularity is also used in TCCN [32], where content is enhanced with tags and nodes keep track of the popularity of each tag as well as how often it is cached in nearby nodes. These popularity-based approaches are quite demanding of node resources, especially memory, since all nodes need to keep track of the global popularity of all content. In addition, approaches that rely on neighbours sharing information to estimate probability would incur an additional communication overhead. These factors make this class of strategies infeasible for the IoT.

Chai et al. [14] propose Betw/EgoBetw, a caching scheme that takes into account the topology of the network, specifically the betweenness centrality of the caching node. Betweenness centrality measures how many times a given node lies on the paths between all pairs of nodes in a given topology. In Chai et al.’s scheme, content is cached at the node with the highest centrality on the delivery path. That way, content
is automatically stored at the most central locations in the network, where Interests are most likely to result in cache hits. However, this strategy requires a costly setup phase. As an alternative, Chai et al. propose the modified version EgoBetw, which requires no setup and instead relies on nodes exchanging connectivity information with their neighbours to approximate their centrality. The trade-off is increased communications and computational overhead during operation, which is antithetical to what IoT algorithms try to accomplish. Thus, it is highly doubtful whether Betw/EgoBetw are feasible for information-centric IoT, and we decided not to implement these strategies for this study.

III. Evaluation

In this section, we present the main contribution of the paper: a comprehensive comparison and evaluation of several caching strategies for information-centric ICN with a focus on latency and hop reduction. For this comparison, we ran a series of experiments on the FIT IoT-LAB [33] open testbed. We used IoT-LAB’s specially developed M3 node1 which has an STM32 (ARM Cortex M3) microcontroller and an Atmel AT86RF231 2.4 GHz transceiver, as our IoT hardware. As firmware for the nodes, we use a simple RIOT-OS [34] application using CCN-lite2 as the ICN implementation, modified to support the different caching strategies.

The experiments were conducted on the Grenoble site3 of the IoT-LAB testbed. The site features about 380 M3 nodes, which are distributed across the rooms and corridors of one floor of an office building. This means that nodes are subject to realistic conditions found in indoor IoT deployments, such as multipath effects, reflection, and absorption caused by walls, doors, and windows made of various materials, as well as unpredictable interference by other wireless signals and people moving around the building. These conditions mean that data gathered will be very close to what might be expected in a real-world deployment.

Of the 380 available nodes, each experiment run is conducted on an arbitrary subset of 50 nodes, chosen randomly each time. This ensures that the topology is different in each experiment run and also that the nodes will not be too strongly connected due to having a large number of one-hop neighbours; this is desirable as it allows us to study the effects of unreliable connections more closely. The transmission range of individual nodes is not enough to reach all other nodes in the building, so communication will be predominantly multihop. In a typical topology generated by this random selection of nodes, the mean path length is between 3 and 4 hops and the maximum is 6 hops. Cache sizes are kept intentionally small; each node’s cache can store up to 5 unique content chunks (all content chunks have the same size).

The experiment is managed by a control script using the IoT-LAB API, which has access to all node caches, outputs, and inputs. An experiment begins with a brief (30 seconds) setup phase, in which every node advertises its own prefix (dictated by its address), which is then propagated through the rest of the network using HoPP’s [35] routing algorithm. HoPP is primarily a publish-and-subscribe scheme for information-centric IoT, but also includes a prefix advertisement mechanism based on the Trickle [36] algorithm. The fact that the routing algorithm is based on Trickle also means that nodes’ Forwarding Information Bases (FIBs) can be kept up to date during runtime. After setup is complete, every node will request a piece of content with a random ID in \( \{0, \ldots, 49\} \) from each of the prefixes in its FIB. Interest and Data packets are handled as specified by the Named Data Networking (NDN) standard. The first time a node receives an Interest for a content chunk it owns, it produces that content chunk (the actual payload is irrelevant for our experiment) and sends it back towards the consumer. Caching of content chunks at intermediate nodes is dictated by the caching strategy selected for the experiment.

The network topology is a direct result of the FIB contents, which in turn are a direct result of the routing algorithm. In the HoPP/Trickle routing algorithm, prefix advertisements are propagated in a tree-like fashion. A producer will advertise its own prefixes with a rank of 0, which is then increased by each node that forwards the advertisement. When forwarding interests, nodes will always prefer the FIB entry with the lowest rank.

The controller takes periodic snapshots of cache contents and FIBs and logs statistics such as latency and hop counts. We use this information to evaluate the caching strategies in the rest of this section.

A. Relation between hop count and latency

Fig. 1 shows how the latency (specifically, the data retrieval delay, which is the time between Interest generation and satisfaction) is affected by the number of hops taken to retrieve the content. This does not differentiate between cached content and content produced by the prefix owner, i.e. the hop count shown here is the number of hops traversed by the Data to the requester from either its original producer or from a caching node. This means that this figure shows only the correlation between hop count and latency for individual transfers, which is linear because nodes are evenly spaced in the network. The caching strategy does not have an impact on this metric in terms of packet travel time, because the caching strategy affects the hop count and not the actual per-hop transfer speed.

The only impact the caching strategy could have on this metric is the computational overhead as each hop on the Data path needs to make a decision. However, the difference appears negligible. Thus, we can already conclude that the complexity of all caching strategies is within acceptable bounds, making them worth considering. For the rest of this paper, this graphic mostly serves to illustrate the ground truth of what latency to expect depending on the hop count. It will be useful for contrasting with the metrics we will discuss in the rest of this section, as it effectively also represents the latencies we would expect if we did not perform any in-network caching at all.

\footnote{1https://github.com/iot-lab/iot-lab/wiki/Hardware_M3-node}
\footnote{2https://github.com/cn-uofbasel/ccn-lite}
\footnote{3https://www.iot-lab.info/deployment/grenoble/}
B. Hop count reduction

For each Interest, we denote the number of hops between its origin and the owner of the prefix it is requesting as the distance to source. In other words, this is the number of hops the Interest/Data packet would always have to travel if there were no caches in the network. We then relate this distance to the actual number of hops taken by the Data packet on the way back. We call this hops to hit as it denotes the number of hops it actually took for the Interest to reach a cache hit. The more efficient a caching strategy, the more content will be available in a cache closer to the consumer, leading to a lower average hops to hit value. The difference between the distance to source and the hops to hit is what we denote as the hop count reduction.

Fig. 4 shows the average hop count reduction for the different caching strategies at different distances. The first obvious effect we can see is that most of the strategies only show a significant hop count reduction starting from a minimum distance to source. In all strategies except for LCD, there is a slight reduction at 3 hops and then a substantial one at 4 hops. The reason for this is that at shorter distances, there is less cache space between the producer and the consumer, which means fewer opportunities for content to be cached on the path. This makes it much more likely that a request will have to be routed all the way to the prefix owner to be satisfied. After a distance of 4 hops, the hops to hit will increase again as the distance to source increases. The “turning point” at which caching begins to have a noticeable impact seems to lie between 3 to 4 hops for most strategies. After this point, there is enough cache space on the path that content is likely to be found at a closer node. LCD, on the other hand, already shows a noticeable hop reduction at a distance of 2 hops, which gets even stronger as the distance increases.

Another strategy that stands out is Labels, which in terms of hop count reduction is second only to LCD. This strategy takes a very different approach from LCD in that it favours an even distribution of content by stratifying it according to content and node IDs [24]. It appears that this approach — explicitly ensuring that each individual piece of content is available in the same number of nodes across the network — results in a beneficial cache distribution.

It has been observed multiple times [12], [13], [20], [37] that CEE is not an optimal caching strategy for ICN, and this is supported by our results. The reason is that CEE is vulnerable to thrashing effects when nodes are caching high volumes of diverse data; the limited size of caches in IoT only exacerbates this effect.

The fact that LCD exhibits a significantly greater reduction
in hop count points to a phenomenon alluded to in Section I: The topology of the network has a significant impact on the effectiveness of the chosen caching strategy. This is explained in more detail in Section III-C:

C. Topology effects

In Section I, we claimed that although caching content closer to the edge (i.e. the consumer) intuitively seems like the better approach, an argument can also be made for the inverse approach. This is because ultimately, the correct decision comes down to the topology of the network. Figs. 2 and 3 illustrate two different network topologies that have very different implications for the effectiveness of different caching policies. Fig. 2 shows what we will call an edge topology where there are multiple individual paths from consumers to the producer that do not intersect at the core of the network, but fray out at the edge. In such a topology, caching closer to the edge (i.e. the consumers) is beneficial because it will save traversal times from the edge to the core. Conversely, Fig. 3 shows what we will call a core topology. Here, the paths between the consumers and the producer intersect near the producer, with each path having only one consumer at the edge. In such a topology, it is better to cache closer to the core (i.e. the producer) because that way, a given cache can serve multiple consumers. Of course, not all possible topologies will fall neatly in one or the other category; mixed topologies with a more even distribution of branching paths are also conceivable.

We can thus see that knowledge of the topology of the given network can be very helpful when deciding on a caching strategy. This, in turn, raises the question: What dictates a network’s topology? In ICN, the answer is simple: The topology is directly informed by the forwarding paths stored in the nodes’ FIBs. The FIBs codify how Interests are forwarded and thus how content is distributed across the network. Thus, to get a sense of a network’s topology, we need to know how its FIBs are constructed. The answer to this is not necessarily universal, since ICN enforces no standards for how FIBs are populated, but in most cases, the contents of the FIBs will be the direct result of the routing algorithm used to advertise content. However nodes learn about their neighbours’ contents and in turn inform their neighbours will shape what their FIBs will look like, which ultimately dictates the entire network’s topology.

The HoPP/Trickle routing algorithm that we use in this evaluation makes the individual FIBs organise themselves into tree topologies based on rank [35]. This means that they resemble a core topology such as the one shown in Fig. 3. Thus, the paths between consumers and producers are more likely to cross closer to the producer, making nodes closer to producers more valuable caching candidates. Our results in Fig. 4 show that a strategy like LCD, which always caches close to the producer, clearly benefits from this fact. We can also see that ProbCache-Inv, which has increased caching probability near the producer, performs a little better than default ProbCache with increased probability towards the consumer, especially at higher distances to source, although this difference is not as pronounced.

Although Labels does not reach the same hop count reduction as LCD does, it should be noted that, unlike that strategy, it is agnostic of topology and thus should be similarly effective in an edge topology, where we would not expect LCD to reach the same performance.

D. Latency and latency reduction

Fig. 5 shows the average content delivery latency in relation to the distance to source. It is immediately obvious that the latencies for different distances follow the same pattern as the hop reduction but are slightly more vertically stretched, which also follows from the measurements shown in Fig. 1: Since the increase in latency with each hop is linear, the predominant change in latency is solely determined by the average hops to hit per distance.

Of course, what we are most interested in is the actual reduction in latency, i.e. how much faster we can retrieve content on average when using a given caching strategy. For this, we compare the average latency of a given strategy by distance to source with the average latency for that number of hops, i.e. the expected latency without caching (cf. Fig. 1). The results are shown in Fig. 6. We can see that the sweet spot in terms of latency reduction, i.e. the distance at which caching has the biggest impact, is found at a distance of 4 hops for all strategies except LCD, where it is 3. This was already implied by Fig. 5, where a distance of 4 (3 for LCD) exhibited the first dip in hop count and thus latency, but when related to the expected latency it becomes even more pronounced.

Once again, LCD shows by far the best performance at the peak, whereas the other strategies are relatively close together. As might be expected, Labels is once again the strongest contender out of the remaining strategies, with ProbCache-Inv coming in third.

E. Overall performance

Figs. 7 to 9 show an overview of the mean hops, the mean latencies, and the mean reduction in latency across all path lengths for the different strategies. We can see that across all strategies, we are able to reduce the mean hops needed for each Interest to a little over 1. Although there are no extreme outliers, CEE, ProbCache, and Prob(p) perform the worst overall, whereas LCD and Labels perform the best. Although default ProbCache performs no better than Prob(p), its inverted variant shows some improvement.

There are several conclusions we can draw from this. The first is that as described above, due to the fact that our chosen routing algorithm results in a core topology, caching near the producer is the more effective policy, making LCD a good choice. From the results, we can also see that strategies that do not take elements of the topology into account (i.e. CEE and Prob(p)) generally do not perform as well as those that do, although Labels goes against that trend. The middle ground is covered by ProbCache-Inv, which does consider topology but still introduces an element of chance. A tentative conclusion from this is that deterministic, topology-based approaches provide better content placement than probabilistic ones.
IV. RELATED WORK

In this section, we will give an overview of existing comparative ICN caching studies with a focus on IoT. Although extensive research has been conducted into caching in ICN, there have been comparatively few studies on caching as it relates to information-centric IoT.

There have been multiple surveys [22], [38], [39] on caching strategies for traditional ICN, as well as a number of comparative studies [22], [23]. Carofiglio et al. have produced a body of work [11], [40]–[42] focusing on latency effects in traditional ICN caching, but their solutions do not address the idiosyncrasies of IoT environments. Caching research focused specifically on information-centric IoT has not had much exposure at the time of writing.

The most comprehensive overview of existing ICN-IoT caching schemes was performed by Arshad et al. [9], [10]. However, this is a purely qualitative survey, and no experimental evaluation of the strategies was performed. The first comparative studies on ICN caching strategies specifically in the IoT were presented by Hail et al. [7] and Meddeb et al. [43]. They used simulated environments to compare several cache decision and cache replacement policies. For our own previous work [37], we took some inspiration from these studies while showcasing a greater number of caching decision and cache replacement strategies and using more performance metrics for our evaluation; we also performed all of our experiments on physical IoT hardware operating in realistic conditions. An important conclusion from our previous study was that cache replacement policies have little to no impact on the performance of ICN-IoT in-network caching, which is why in this study, we focus exclusively on caching decision policies.

To the best of our knowledge, no previous study has explicitly taken the effects of the routing algorithm and the network topology into account when evaluating in-network caching strategies for information-centric IoT, and no other comparative study apart from our own previous research has been performed using physical IoT hardware.

V. CONCLUSIONS AND FUTURE WORK

We have presented a comparison and evaluation of several different caching strategies for information-centric IoT, focusing on their effects on content delivery latency. Our results indicate that the topology of the network has an impact on which cache distribution is optimal, and thus it may be fruitful to use caching algorithms that are optimised for the given topology. However, caching strategies that ignore topology in favour of other approaches, such as stratifying the data evenly across the network, are also promising and may be preferable if the topology is unknown, mutable, or a hybrid between different types. The network topology is influenced by the choice of routing algorithm, thereby creating a direct link between routing algorithm and caching strategy. In other words, a holistic caching solution for information-centric IoT should take all of these aspects into account.

Of course, determining the optimal caching strategy for a given IoT application also depends on the requirements of that particular application as well as the constraints imposed by the hardware. More computationally intensive caching strategies may yield better results, but may take too much resources away from the actual application. Overall, however, our results indicate that even simple caching strategies such as LCD or Labels can improve performance compared to indiscriminate caching, so they will almost always be worth considering.

The direct link between the choice of routing algorithm and the effectiveness of the caching strategy is a phenomenon that, to the best of our knowledge, has not been explicitly investigated in ICN caching research to date. Most research that compares caching strategies does not take the routing algorithm into account at all; often, FIBs are just assumed to be populated a priori. We believe that an in-depth comparison of caching strategy performance on topologies created by different routing algorithms would yield valuable insights and pave the way towards a holistic solution. Similarly, future research should focus more strongly on different topologies likely to be encountered in IoT deployments and how they affect the choice of caching strategy. Therefore, our future work will have the aim of comparing the effectiveness of different caching strategies in core topologies as well as edge topologies, and work towards caching solutions that are effective regardless of topology.

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