An Ant Colony Inspired Cache Allocation Mechanism for Heterogeneous Information Centric Network

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ABSTRACT The cache allocation of in-network caching is fundamental to the quality of service in heterogeneous information centric network (ICN). The aim of the cache allocation is to efficiently allocate appropriate cache capacity to each router for storing content, avoiding the long-distance transmission cost from clients to servers. Existing works focus on the analysis of network topology. However, this way is computation-expensive for such analysis, at the same time it cannot reach a completely optimal network, due to its used multiple conflicting performance metrics. In this paper, we propose an ant colony inspired cache allocation mechanism (ACCM) for heterogeneous ICN, which is able to deal with the cache budget constraint. Specifically, we first construct an evaluation model of network performance, in terms of hit ratio, energy consumption, time latency, and throughput. Then, based on the evaluation model, we devise an ant colony inspired cache allocation mechanism, where the ICN topology system is mapped into an ant colony system and the cache allocation process is simulated by the ant colony foraging behavior. Our theoretical analysis shows that the proposed mechanism can converge to the best solution. Finally, we conduct simulations on AttMpls and TW Telecom topologies with real datasets in YouTube. Simulation results show the effectiveness and efficiency of the proposed mechanism on the simulation instances in terms of hit ratio, energy consumption, time latency, and throughput.

INDEX TERMS Heterogeneous ICN, cache allocation, ant colony.

I. INTRODUCTION

Information Centric Network has emerged as a novel network paradigm, which caches contents provided by servers at routers to serve users. Compared with the traditional host-centric network, the outstanding advantage of ICN is in-network caching, where each router is able to store contents [1]. Since ICN routers cache diverse contents from servers, contents requested from users are responded by routers that has stored requested contents, which avoids long-distance transmission cost from clients to servers and improves response speed substantially. Aiming at in-network caching in ICN, the cache allocation is fundamental to cache contents, which allocates cache capacity to each router [2], [3]. Especially, in the heterogenous ICN, the cache allocation becomes more complex and difficult because each router can employ different sizes of cache capacity [4]. In addition, equipping cache capacity for routers is extremely expensive in terms of cost and energy consumption, so it is unnecessary and wasteful to distribute large cache capacity for all routers. Therefore, the appropriate cache allocation scheme is significant for heterogenous ICN to optimize network performance and reduce cost.

With regard to the cache allocation, two main aspects should be taken into consideration for heterogenous ICN [5]. The one is the centrality degree in network topology, and the router with the higher centrality degree is supposed to be allocated larger cache capacity. The other is the requested popularity, larger cache capacity is distributed to the router requested more frequently. However, based on both above...
considerations, the cache allocation requires amounts of computations, which is difficult for heterogeneous ICN to obtain the optimal cache allocation scheme.

Many investigations have conducted on cache allocation for heterogeneous ICN, which are mainly divided into two categories [6]–[9]. One category is cache capacity is allocated to each router proportionally according to its importance degree, which is related to centrality degree and requested frequency. Another category is to formulate the cache allocation problem as an optimization problem according to network performance, and the solution is obtained through solving optimization problem. However, both of the above categories have some limits. First of all, these cache allocation methods are expensive in aspects of computation and complexity, involving complex processes to analyze network topology or solve the optimization problem [10], [11]. In addition, the solutions obtained by existing mechanisms cannot reach a completely optimal network [12], considering multiple conflicting performance metrics, such as hit ratio and energy consumption.

Recently, with the study on the bionics and application of evolutionary algorithms [11], [13], bionic methods have been applied to ICN. Some investigations have conducted on ant colony optimization bionic ICN, which have shown that characteristics of ant colony system are suitable for ICN. However, these investigations focus on ICN routing mechanism, and cache allocation problem in heterogeneous ICN have not been addressed with bionic algorithms.

The motivations of our work are as follows:

• In order to optimize network performance in heterogeneous ICN, an appropriate evaluation model of network performance is the basis for ICN to evaluate the quality of the cache allocation solutions. Hit ratio, energy consumption, time latency, and throughput are four significant metrics of network performance, which evaluate accuracy, cost, and quality of service comprehensively.

• Multiple factors are supposed to be considered for the cache capacity of routers in heterogeneous ICN, such as centrality and content popularity. Due to multiple factors, complex computations are required for cache allocation. Since ant colony is able to find the best solution heuristically and ant colony bionic ICN is effective, we propose a cache allocation mechanism inspired by ant colony system for heterogeneous ICN.

Based on the above considerations, in this paper, we propose an ant colony inspired cache allocation mechanism named ACCM for heterogeneous ICN to address the cache allocation problem under the constraint of cache budget. Specifically, we first construct an evaluation model of the network performance, considering hit ratio, energy consumption, time latency, and throughput as metrics. Then, we devise an ant colony inspired cache allocation mechanism, where the ICN topology system is mapped into an ant colony system and the cache allocation process is simulated by the ant colony foraging behavior. Our theoretical analysis shows that the proposed mechanism is able to converge to the best cache allocation scheme for heterogeneous ICN.

The contributions of this paper are summarized as follows:

• We construct an evaluation model of network performance to evaluate the quality of solutions, regarding hit ratio, energy consumption, time latency, and throughput as network performance metrics.

• Based on the performance evaluation model, we design an ant colony inspired cache allocation mechanism to allocate cache capacity to routers. To our best knowledge, it is the first time to design an ant colony bionic method to deal with the cache allocation problem for heterogeneous ICN. The proposed bionic mechanism obtains the solution with the best network performance heuristically without complex analysis and computation.

• We conduct a strong theoretical analysis to show that ant colony is able to converge to the cache allocation scheme with the best network performance in heterogeneous ICN.

The rest of this paper is organized as follows: Section II introduces the related work of the paper. Section III constructs models of cache allocation problem and network performance. Section IV proposes an ant colony inspired cache allocation mechanism for heterogeneous ICN and conducts theoretical demonstrations to show the effectiveness of the proposed mechanism. Section V conducts simulations to analyze the effectiveness and efficiency of ACCM and compares the proposed mechanism with two algorithms. Section VI summarizes this paper.

II. RELATED WORK

This section introduces the related work of existing cache allocation algorithms in heterogeneous ICN, which can be divided into two categories. The one is to allocate cache capacity to routers proportionally according to the importance of routers. The other is to formulate cache allocation as the performance optimization problem and obtain the optimal solution as the cache allocation scheme. We introduce the related work of cache allocation algorithms from the above two categories in the following.

There have been some cache allocation methods based on the importance of each router. Rossi and Rossini [14] studied the difference of performance based on different centrality metrics and proved that Degree-Centrality is the best performance metric for cache allocation. Hagikura et al. [15] studied the relationship between network performance of optimal cache allocation and several factors including network topology, network space, and etc. And this paper proposed an approximate model to present the unpredictability of optimal cache allocation. Wang et al. [16] investigated different effects of several factors on cache allocation and network performance and proposed a centrality-based heuristic method to find a feasible and approximate optimal cache allocation solution in ICN. Lal and Kumar [17] proposed an algorithm based on centrality metrics to evaluate router centrality,
combining Closeness-Centrality, Reach-Centrality, Degree-Centrality, and Between-Centrality four indicators, and allocated cache capacity to each router proportionality according to the centrality. However, this category of cache allocation methods has to analyze the importance of each node in the whole network, which is involved in many aspects, such as node centrality, node popularity, and et al. Especially for large-scale and complex networks, this algorithm is expensive in terms of computations and complexity [11].

Some studies on formulating the cache allocation problem as an optimization problem to obtain the optimal solution have been conducted. Yuan et al. [18] used the distribution fairness based on the hit ratio and time delay as the evaluation indicators to establish an optimization model, and then used a heuristic algorithm to solve the optimization model to address the cache allocation problem. Mai et al. [19] developed a distributed adaptive algorithm to solve the maximization model of network performance. Under constraints of cache budgets, capacity of routers can be dynamically allocated. Banerjee et al. [20] used a greedy algorithm to select relatively high-popular content to cache, and the upstream cache took the missed downstream requests into account to maximize the hit ratio. Qazi et al. [21] proposed the opt-Cache mechanism to determine optimal content placement scheme under certain constraints, which established an optimization model related to minimizing the latency firstly and then proposed a heuristic method to obtain the optimal scheme.

Zhao and Lv [11] used energy consumption, router load, hit ratio, and throughput as performance evaluation metrics to establish an optimization model, and then the cache allocation problem was transformed into a 0-1 knapsack problem. The optimal solution is obtained by solving the knapsack problem, which used a heuristic method based on the expected efficiency of the ant colony. Since these methods obtain solutions by formulating cache allocation as the optimization problem, and optimization algorithms require numerous computations [15], [22], this category of methods is computationally complex. And cache allocation solutions obtained by these methods cannot reach a completely optimal network, due to multiple conflicting performance metrics, such as hit ratio, throughput, and energy consumption.

The above-mentioned cache allocation methods can allocate cache capacity to routers in heterogeneous ICN. However, the cache allocation schemes obtained by these methods are computation-expensive for network analysis or solving optimization problems. In this paper, we propose an ant colony inspired cache allocation mechanism to optimize network performance. The ant colony and its foraging behavior are used to simulate ICN topology and the process of cache allocation respectively. And the path that ant colony converges to eventually is the cache capacity allocation solution for ICN correspondingly.

III. PROBLEM MODELING

This section constructs an evaluation model of network performance to evaluate the quality of cache allocation solutions. Firstly, the cache allocation problem in heterogeneous ICN is modeled, considering hit ratio, energy consumption, time latency, and throughput as network performance metrics. Then, the process of metrics quantifications is given. Finally, the evaluation model of network performance is established based on metrics.

A. CACHE ALLOCATION MODEL

The heterogeneous ICN topology with n content routers is abstracted as $G (V, E, C)$, where $V$ represents the set of content routers, $E$ represents the set of edges between routers, and $C$ represents the set of cache capacity to routers. $V$, $E$, and $C$ are defined as follows:

$V = \{ CR_i \} | 1 \leq i \leq n \}$
$E = \{ e_{ij} \} | 1 \leq i, j \leq n \}$
$C = \{ c_i \} | 1 \leq i \leq n \}$

(1)

where $CR_i$ represents the content router $i$, $e_{ij}$ represents the edge between $CR_i$ and $CR_j$, and $c_i$ represents the allocated capacity at $CR_i$. $CR_i$ and $e_{ij}$ are further defined as follows:

$CR_i = \{ CR_i^{c_i} | 1 \leq i \leq n, 1 \leq c_i \leq C_{max} \}$
$e_{ij} = \{ e_{ij}^{c_i,c_j} | 1 \leq i, j \leq n, 1 \leq c_i, c_j \leq C_{max} \}$

(2)

where $CR_i^{c_i}$ represents the $CR_i$ with cache capacity $c_i$, $e_{ij}^{c_i,c_j}$ represents the edge between $CR_i^{c_i}$ and $CR_j^{c_j}$, and $C_{max}$ is the maximum cache capacity of each router.

Based on the model of ICN topology, cache allocation can be defined as: Given the constraint of cache capacity, cache allocation is to allocate capacity to each router to reach the best network. We consider time latency, energy consumption, hit ratio, and throughput as metrics to optimize network performance. We use $t_i$, $e_i$, $hr_i$, and $tp_i$ to represent time latency, energy consumption, hit ratio, and throughput of $CR_i$ with a unit size of cache capacity respectively, and the performance metrics of cache allocation is modeled as:

Minimize $T_{total} = \sum_{i=1}^{n} t_i c_i$
Minimize $E_{total} = \sum_{i=1}^{n} e_i c_i$
Maximize $H_{total} = \sum_{i=1}^{n} hr_i c_i$
Maximize $TP_{total} = \sum_{i=1}^{n} tp_i c_i$

(3)

where $c_i = \{ 0, 1, 2, \ldots, C_{max} \}$, and $c_i = 0$ means that $CR_i$ has no cache capacity. $T_{total}$, $E_{total}$, $H_{total}$, and $TP_{total}$ represents the overall time latency, energy consumption, hit ratio, and throughput respectively.

Our mechanism is to obtain the set of $C = \{ c_1, c_2, \ldots, c_n \}$ to achieve the best network performance with the lowest time latency and energy consumption, and the highest hit ratio and throughput in the network.
In the end, the model of cache allocation in heterogeneous ICN is established as:

\[
\begin{align*}
\text{Minimize } & T_{\text{total}} = \sum_{i=1}^{n} t_i c_i \\
\text{Minimize } & E_{\text{total}} = \sum_{i=1}^{n} ec_i c_i \\
\text{Maximize } & H_{\text{total}} = \sum_{i=1}^{n} hr_i c_i \\
\text{Maximize } & TP_{\text{total}} = \sum_{i=1}^{n} tp_i c_i \\
\text{Subject to } & c_i \leq C_{\text{max}} \\
\text{Subject to } & \sum_{i=1}^{n} c_i \leq C_{\text{total}}
\end{align*}
\]

where \(C_{\text{total}}\) represents the maximum total cache capacity of all routers in the network.

**B. METRICS QUANTIFICATION**

This section is to quantify evaluation metrics \(t_i, ec_i, hr_i, \) and \(tp_i, t_i\) refers to the time latency of \(CR_i\), including processing time and transmission time. The processing time is spent by processing data, and transmission time is spent by transmitting data from the content router to the request client. \(t_i\) is defined as:

\[
t_i = t_{\text{pro}}^i + t_{\text{trans}}^i
\]

where \(t_{\text{pro}}^i\) is the processing time on \(CR_i\), and \(t_{\text{trans}}^i\) is the transmission time spent by transmitting data from \(CR_i\) to request client.

\(ec_i\) refers to the energy consumption of \(CR_i\), including two parts: hardware and transmission. The hardware consumption is caused by router caching contents, and transmission consumption refers to the energy consumption caused by the router transferring contents. \(ec_i\) is defined as:

\[
ec_i = P_i t_i + \varphi tra_i
\]

where \(P_i\) is the fixed hardware cache energy consumption of the \(CR_i\) when \(CR_i\) caches the unit byte size content, \(\varphi\) is the energy consumption corresponding to \(CR_i\) transmitting the unit byte size content, \(t_i\) is the running time of \(CR_i\), and \(tra_i\) is the traffic size of the content transmitting through \(CR_i\).

\(hr_i\) refers to the ratio of the number of requests successfully responded to the number of requests received by \(CR_i\). \(hr_i\) is defined as:

\[
hr_i = \frac{N_{\text{hit}}}{N_{\text{req}}}
\]

where \(N_{\text{hit}}^i\) represents the number of requests hitting contents successfully on \(CR_i\), and \(N_{\text{req}}^i\) represents the number of requests received by \(CR_i\).

\(tp_i\) refers to the transferred traffic in a unit time of \(CR_i\), and is defined as:

\[
tp_i = \frac{tra_i}{t_i}
\]

**C. PERFORMANCE EVALUATION MODEL**

To calculate the performance of the network in a direct method, time latency, energy consumption, hit ratio, and throughput are integrated into the comprehensive network performance. And \(NetP_i\) is used to represent the comprehensive network performance of \(CR_i\) caching the unit byte size content.

Based on the \(t_i, ec_i, hr_i, \) and \(tp_i, NetP_i\) is defined as:

\[
NetP_i = \omega(1 + hr_i + tp_i) - \gamma(ec_i + t_i)
\]

where \(\omega\) and \(\gamma\) are weight coefficients, which determine the importance of hit ratio, throughput, energy consumption, and time latency. And \(\omega > 0\) and \(\gamma > 0\), because network performance is proportional to hit ratio and throughput, and is inversely proportional to time latency and energy consumption.

For the cache allocation to routers in heterogeneous ICN, our objective is to obtain the cache allocation solution with the best comprehensive network performance. The evaluation model of network performance is established and defined as follows:

\[
\begin{align*}
\text{Maximize } & NetP_{\text{total}} = \sum_{i=1}^{n} NetP_i c_i \\
\text{Subject to } & c_i \leq C_{\text{max}} \\
\text{Subject to } & \sum_{i=1}^{n} c_i \leq C_{\text{total}}
\end{align*}
\]

where \(NetP_{\text{total}}\) is the overall network performance, related to time latency, energy consumption, hit ratio, and throughput of all content routers in the network.

Based on the above model, our object is described specifically as: Under constraints of \(C_{\text{max}}\) and \(C_{\text{total}}\), a cache allocation scheme is required to maximize comprehensive network performance of all routers in ICN.

**IV. ANT COLONY INSPIRED CACHE ALLOCATION MECHANISM**

The ant colony algorithm is inspired by the biological behavior of ant colony foraging. With naturally self-adaptive and supporting mobility [23], ant colony can find the shortest path from the nest to the food spontaneously. This section first introduces how to employ ant colony to simulate ICN. Next, based on the performance evaluation model, we adopt a bionic method and propose an ant colony inspired cache allocation mechanism to address the cache allocation problem for heterogenous ICN. In addition, we give a strong theoretical analysis to show the proposed ant colony inspired cache allocation mechanism can converge to the cache allocation scheme with the best network performance.

**A. ANT COLONY BIONIC ICN**

Ant colony algorithm was proposed by Marco Dorigo in 1991 based on the experiments of ant colony searching for food [24]. In the process of ant colony foraging, ants release chemical substances on the way back according to the quality of food, which is defined as pheromone and dissipates gradually over time. Ant colony searches for food according to the pheromone concentration. The path with higher
pheromone concentration attracts more ants, meanwhile more ants result in higher pheromone concentration released on the path, thus a positive feedback mechanism of ant colony foraging is formed. Eventually, the ant colony converges to the shortest path from nest to food according to pheromone concentration.

Due to naturally self-adaptive and supporting mobility in the ant colony system [25], we map an ant colony into ICN and employ ant colony foraging behavior to simulate the process of cache allocation in ICN. Focusing on the characteristics of ICN and the ant colony system respectively, reasons for employing ant colony system to simulate ICN are explained from two aspects.

(1) Behavior: Both ICN and the ant colony system search for the solution based on a metric. From the aspect of ICN, the cache capacity of each router is searched for according to network performance, in terms of hit ratio, energy consumption, time latency, and throughput. From the aspect of ant colony system, the location is searched for according to pheromone concentration calculated by distance of the path. Pheromone concentration is used to simulate network performance, and the converged path of the ant colony with the highest pheromone concentration is the cache allocation scheme with the best network performance.

(2) Goal: Both ICN and the ant colony system expect to obtain the best solution. For ICN, the cache allocation solution for routers with the best network performance is expected. For ant colony, the best path with the shortest distance is required. An ant colony is employed to simulate ICN, and the path with the shortest distance is the cache allocation solution for routers with the best network performance in ICN correspondingly.

Therefore, the ant colony system is feasible to simulate ICN, where ant colony is mapped into ICN topology, and ant colony foraging behavior is used to simulate the process of cache allocation in ICN. From the perspective of ICN, the cache allocation solution for routers to optimize network performance is required; From the perspective of the ant colony, the ant colony converges to the best path with the highest pheromone concentration. Correspondingly, the set of locations in the path to which ant colony converges is the best cache allocation solution in ICN. The corresponding relationship between the ant colony system and ICN is shown in Fig. 1.

In this paper, an ant colony is mapped into ICN topology and ant colony foraging behavior is used to simulate the process of cache capacity allocation to routers. Specifically, the ant simulates the cache capacity, the location on the path in the ant colony simulates the location of each router in ICN, and the pheromone concentration simulates network performance. The process of ant colony searching for the path with the shortest distance according to pheromone concentration is used to simulate the process of content searching for cache capacity allocation with the best performance according to network performance. As the ant colony iterates, the set of locations in the path with the shortest distance obtained by the ant colony is the cache allocation scheme with the best network performance for ICN correspondingly.

B. ANT COLONY FOR CACHE ALLOCATION

In the proposed mechanism, the ant colony is mapped into the ICN topology, and the ant colony foraging behavior is used to simulate the process of cache allocation. Based on the above ant colony bionic ICN, we introduce the design of ant colony foraging behavior for cache allocation mechanism in ICN in the following.

In the process of searching for the best cache allocation solution in the ant colony, ants release pheromone on the visited path according to the performance evaluation model, and the pheromone remaining on the path evaporates at a certain speed with the iterations. We use $\tau_{ij}^{c(e)}(t)$ to represent total pheromone concentration remaining on the path $e_{ij}^{c(e)}$ in generation $t$, and $\Delta \tau_{ij}^{c(e)}(t)$ to represent the pheromone concentration released by ants $\lambda$ on the path $e_{ij}^{c(e)}$ in generation $t$. The update strategy of the pheromone concentration is defined as:

$$\tau_{ij}^{c(e)}(t) = \rho(t)\tau_{ij}^{c(e)}(t-1) + \Delta \tau_{ij}^{c(e)}(t)$$  \hspace{1cm} (11)

where $\rho(t)$ is the remaining pheromone concentration ratio of the generation $t$. The alcohol volatilization model is used to simulate the reducing process of pheromone. In the alcohol volatilization model, the smell of alcohol gradually reduces with time going by, that is, the alcohol concentration gradually decreases. In the process of ant colony foraging, the pheromone released by ants cannot stay on the path all the time, and it will gradually decrease and reduce the attraction to ants. Therefore, the alcohol volatilization model is similar to the recession process of pheromone, and we use the alcohol volatilization model to simulate the recession of pheromone [25]. The pheromone remaining on the path volatilizes with iteration, and the remaining pheromone is defined as:

$$\rho(t) = e^{-\theta t}$$  \hspace{1cm} (12)

where $\theta$ is the adjustment coefficient of pheromone volatilization speed.
In formula (9), $\Delta \tau_{ij}^{c(l)}(t)$ is the total quantity of the pheromone released by ants passing through $e_{ij}^{c(l)}$ in generation $t$. The pheromone quantity released by the ant $\lambda$ on $e_{ij}^{c(l)}$ is related to comprehensive network performance of the router $CR_i^l$ and $CR_j^l$. $\Delta \tau_{ij}^{c(l)}(t)$ is defined as:

$$\Delta \tau_{ij}^{c(l)}(t) = \sum_{\lambda=1}^{n} (Q \times NetP_{\lambda}, \mu_{ij}^\lambda)$$

(13)

where $\mu_{ij}^\lambda = \{0, 1\}$, if the ant $\lambda$ passes through $e_{ij}$ in the generation $t$, $\mu_{ij}^\lambda = 1$; otherwise $\mu_{ij}^\lambda = 0$. $NetP_{\lambda}$ represents the comprehensive network performance of ant $\lambda$ in the current path. $Q$ represents the increasing coefficient of pheromone concentration.

The transferring probability of ants is not only related to the pheromone concentration, but also involving the performance of the router itself, which can prevent the ant colony from converging to a locally optimal solution. We use $\eta_{ij}^{c(l)}$ to represent the heuristic information between $CR_i^l$ and $CR_j^l$, which is related to the comprehensive network performance of $CR_i^l$ and $CR_j^l$. $\eta_{ij}^{c(l)}$ is defined as:

$$\eta_{ij}^{c(l)} = \sigma \times (NetP_{ij} \times c_i + NetP_{ij} \times c_j)$$

(14)

where $\sigma$ is the adjustment coefficient, $NetP_{ij}$ and $NetP_{ij}$ represent the comprehensive network performance of $CR_i$ and $CR_j$ with unit byte size of cache capacity respectively.

According to pheromone concentration and heuristic information on the path, $p_{ij}^{c(l)}$ represents the probability of ant $\lambda$ choosing $CR_j^l$ when it locates at $CR_i^l$. $p_{ij}^{c(l)}$ is defined as:

$$p_{ij}^{c(l)} = \frac{[\tau_{ij}^{c(l)}(t)]^\alpha \eta_{ij}^{c(l)}]^{\beta}}{\sum_{CR_i \in N_i^l} [\tau_{ik}^{c(l)}(t)]^\alpha [\eta_{ik}^{c(l)]]}^{\beta}}$$

(15)

where $N_i^l$ represents the set of routers that ant $\lambda$ has not visited positioning at $CR_i$, $\alpha$ and $\beta$ are the heuristic factors of pheromone concentration and heuristic information respectively, which determine the relative importance of pheromone concentration and heuristic information respectively. And pheromone concentration and heuristic information determine the transferring probability of each ant collaboratively.

Based on the above process, each ant chooses a router to visit according to the transferring probability, in terms of pheromone concentration and heuristic information. And the ant colony stops searching until the cache capacity of routers on the path does not satisfy the cache capacity constraint. With the iterations, ant colony converges to the path with the highest pheromone concentration corresponding to the best network performance, in terms of time latency, energy consumption, hit ratio, and throughput, and the set of routers on the path is the best cache allocation scheme. The ant colony inspired cache allocation mechanism is described in Algorithm 1.

Algorithm 1 Ant Colony Inspired Cache Allocation Mechanism

**Input:** $N$, $I_{max}$, $C_{max}$, $C_{total}$

**Output:** $C_{best} = \{c_1, c_2, \ldots, c_n\}$

1: For $t = 1$ to $I_{max}$
2: For $\lambda = 1$ to $N$
3: Initialize the position of ant $\lambda$, pheromone concentration, $C_{best}$, and $P_{best}$
4: While $C < C_{total}$
5: Calculate $\tau_{ij}^{c(l)}$ according to formula (14)
6: Calculate $p_{ij}^{c(l)}$ (t) according to formula (15)
7: Select router to visit according to $P_{ij}^{c(l)}(t)$
8: end while
9: Ant $\lambda$ obtains best cache allocation solution $C_{\lambda}$ and best performance $P_{\lambda}$
10: end for
11: Calculate $\Delta \tau_{ij}^{c(l)}(t)$ according to formula (13)
12: Update $\tau_{ij}^{c(l)}(t)$ according to formula (11)
13: Ant colony obtains the best cache allocation solution $C_t$ and best performance $P_t$ in generation $t$
14: If $P_t > P_{best}$
15: $C_{best} = C_t$
16: end if
17: end for
18: $C_{best}$ is the best cache allocation solution for ICN

C. THEORETICAL ANALYSIS

In the proposed mechanism, an ant colony chooses the path heuristically based on the evaluation model of network performance. And the ant colony is capable of converging to the routes to optimize network performance. This section conducts a theoretical analysis to show that ant colony is able to converge to the best cache allocation scheme.

We give some illustrations before theoretical analysis. Assuming there are $n$ routes for ant colony with $m$ ants, namely: $l_1, l_2, \ldots, l_n$, corresponding to network performance of cache allocation scheme on each route, namely: $NetP_{l_1}$, $NetP_{l_2}$, $\ldots$, $NetP_{l_n}$. We suppose that the route corresponding to the best cache allocation scheme is $l_1$. Therefore, for $1 \leq i \leq n$ and $i \neq a$, we can get $NetP_{l_a} > NetP_l$. We use $q_i^l$ and $p_i^l$ to represent average pheromone concentration and average transferring probability of $l_i$ after generation $t$. And the pheromone concentration on each path is set to $C$ at the beginning.

Theorem 1: If $\alpha \geq 0$ and $\beta \geq 0$, for $1 \leq i \leq n$ and $i \neq a$, $p_i^a > p_i^l$ and $q_i^l > q_i^a$.

The demonstrations are given in the following:

$$p_i^l = \frac{[\tau_i(0)]^\alpha [\eta_i]^\beta}{\sum_{j=1}^{n} [\tau_j(0)]^\alpha [\eta_j]^\beta} = \frac{C^\alpha [\sigma \times NetP_i]^\beta}{\sum_{j=1}^{n} C^\alpha [\sigma \times NetP_j]^\beta}$$

(16)

where $NetP_a > NetP_l$, $p_i^0 > p_i^a$ holds.

$$q_i^l = \rho (1 + C \times m \times p_i^l \times Q \times NetP_i)$$

(17)
where $NetP_a > NetP_i$ and $p_i^0 > p_i^0$, $q_i^1 > q_i^1$ holds.

$$P_i^1 = \frac{[\tau_i(t)]^\alpha(\eta_i)\beta}{\sum_{j=1}^{n} [\tau_j(t)]^\alpha(\eta_j)\beta} = \frac{(q_i^1)^\alpha(\sigma \times NetP_i)^\beta}{\sum_{j=1}^{n} (q_j^1)^\alpha(\sigma \times NetP_j)^\beta}$$  \hspace{1cm} (18)$$

where $NetP_a > NetP_i$ and $q_i^1 > q_i^1$, $P_i^1 > P_i^1$ holds.

According to mathematical induction, we can arrive the conclusion:

$$q_i^1 = \rho(t) \times q_i^{-1} + mp_i^1 Q \times NetP_i$$  \hspace{1cm} (19)$$

$$P_i^1 = \frac{[\tau_i(t)]^\alpha(\eta_i)\beta}{\sum_{j=1}^{n} [\tau_j(t)]^\alpha(\eta_j)\beta} = \frac{(q_i^1)^\alpha(\sigma \times NetP_i)^\beta}{\sum_{j=1}^{n} (q_j^1)^\alpha(\sigma \times NetP_j)^\beta}$$  \hspace{1cm} (20)$$

where, based on the above demonstrations, it can be seen clearly that $q_i^1 > q_i^1$ and $p_i^1 > p_i^1$.

It can be seen from Theorem 1 that the cache allocation scheme with the best network performance has the highest pheromone concentration and probability to be chosen in each iteration.

**Theorem 2**: If $\alpha \geq 1$ and $\beta \geq 0$, for $1 \leq i \leq n$ and $i \neq a$,

$p_i^0 > p_i^0$.

The demonstrations are given in the following:

$$P_i^0 = \frac{[\tau_i(t)]^\alpha(\eta_i)\beta}{\sum_{j=1}^{n} [\tau_j(t)]^\alpha(\eta_j)\beta} = \frac{1}{1 + \sum_{j=1}^{n} (q_i^0)^\alpha(\sigma \times NetP_j)^\beta}$$  \hspace{1cm} (21)$$

$$P_i^{0-1} = \frac{[\tau_i(t)]^\alpha(\eta_i)\beta}{\sum_{j=1}^{n} [\tau_j(t)]^\alpha(\eta_j)\beta} = \frac{1}{1 + \sum_{j=1}^{n} (q_i^{0-1})^\alpha(\sigma \times NetP_j)^\beta}$$  \hspace{1cm} (22)$$

$$\frac{1}{P_i^0} - \frac{1}{P_i^{0-1}} = \sum_{j=1,j\neq a}^{n} \frac{NetP_j^\beta}{NetP_a^\beta} [(\frac{q_j}{q_a})^\alpha - (\frac{q_j^{0-1}}{q_a^{0-1}})^\alpha]$$  \hspace{1cm} (23)$$

We show $\frac{1}{P_i^0} - \frac{1}{P_i^{0-1}} < 0$ to prove $P_i^0 > P_i^{0-1}$. As is known $\alpha \geq 1$, it can be seen clearly that if $(\frac{q_j}{q_a})^\alpha - (\frac{q_j^{0-1}}{q_a^{0-1}})^\alpha < 0$, $(\frac{q_j}{q_a})^\alpha - (\frac{q_j^{0-1}}{q_a^{0-1}})^\alpha < 0$ holds, and $\frac{1}{P_i^0} - \frac{1}{P_i^{0-1}} < 0$ holds.

$$\frac{q_i^1}{q_i} - \frac{q_i^{0-1}}{q_i^{0-1}} = \frac{m \times Q \times (p_i^{0-1} \times q_i^{0-1} \times NetP_i - p_i^{0-1} \times q_i^{0-1} \times NetP_a)}{q_i^{0-1} \times [\rho(t) \times q_i^{0-1} + m \times P_i^{0-1} \times Q \times NetP_a]}$$  \hspace{1cm} (24)$$

It can be seen from formulation (24) that if $p_i^{0-1} \times q_i^{0-1} \times NetP_i - p_i^{0-1} \times q_i^{0-1} \times NetP_a > 0$, $\frac{q_i^1}{q_i} - \frac{q_i^{0-1}}{q_i^{0-1}} < 0$ holds.

$$p_i^{0-1} q_i^{0-1} - p_i^{0-1} q_i^{0-1} - q_i^{0-1} \times NetP_a$$

$$= q_i^{0-1} q_i^{0-1} (NetP_i - p_i^{0-1} \times q_i^{0-1} \times NetP_a)$$

$$\frac{q_i^{0-1} q_i^{0-1} (NetP_i - p_i^{0-1} \times q_i^{0-1} \times NetP_a)}{\sum_{j=1}^{n} (q_j^{0-1})^\alpha(NetP_j)^\beta}$$  \hspace{1cm} (25)$$

where, $q_i^{0-1} < q_i^{0-1}$ and $NetP < NetP_a$, which have been demonstrated in Theorem 1. Under the constraints of $\alpha \geq 1$ and $\beta \geq 0$, $p_i^{0-1} \times q_i^{0-1} \times NetP_i - p_i^{0-1} \times q_i^{0-1} \times NetP_a > 0$. So $p_i^0 > p_i^{0-1}$ is demonstrated.

Theorem 2 shows that an ant colony chooses the best route $l_a$ in an increasing probability with the iterations.

**Theorem 3**: If $\alpha \geq 1$ and $\beta \geq 0$, $\lim_{t \to \infty} P_i^a = 1$.

As is shown in Theorem 2 that $\frac{q_i}{q_i^{0-1}} \times q_i^{0-1} \times NetP_a$, so $\frac{q_i}{q_i^{0-1}} \to 0$, when $t \to \infty$. $\lim_{t \to \infty} P_i^a$ is computed as follows:

$$\lim_{t \to \infty} P_i^a = \lim_{t \to \infty} \frac{\sum_{j=1}^{n} (q_j^a)^\alpha(\sigma \times NetP_a)^\beta}{\sum_{j=1}^{n} (q_j^a)^\alpha(\sigma \times NetP_j)^\beta}$$

$$= \frac{1}{1 + \sum_{j=1,j\neq a}^{n} (\frac{q_j^a}{q_a^a})^\alpha(NetP_j)^\beta} = 1$$  \hspace{1cm} (26)$$

Theorem 3 shows that with iterating, an ant colony chooses the route corresponding to the best cache allocation scheme with the probability close to 1.

Based on the above demonstrations, under the constraints of $\alpha \geq 1$ and $\beta \geq 0$, with iterating, an ant colony converges to the best route with the probability close to 1. Therefore, based on the theoretical analysis, it can be considered that the proposed ant colony inspired cache allocation mechanism for heterogeneous information centric network is able to obtain the cache allocation scheme with the best network performance for heterogeneous ICN.

**V. SIMULATION ANALYSIS**

In this section, we conduct simulations on the proposed mechanism to prove the effectiveness of the mechanism. Next, comparison simulations are conducted on our mechanism and the other two algorithms in terms of energy consumption, hit ratio, time latency, and throughput. And the analysis of results shows that our mechanism performs better than the other two algorithms on cache allocation for heterogeneous ICN.

**A. SIMULATION SETUP**

The ant colony inspired cache allocation mechanism for heterogeneous ICN is implemented from two parts: one is to deploy network topology and establish an evaluation model of performance, considering energy consumption, hit ratio, time latency, and throughput as metrics; The other is to design the ant colony inspired algorithm to allocate cache capacity to...
routers. The simulations are conducted on MATLAB with a computer configured with Intel(R) Core (TM)i5-9400F, CPU 2.90 GHz, 8GB RAM.

The simulations are implemented on two real network topologies, a small network topology AttMpls (25 nodes, 56 edges) [26] and a medium network topology TW Telecom (76 nodes, 115 edges) [27], as shown in Fig. 2 and Fig. 3 respectively. And the simulations are driven by the real dataset in YouTube [28], which is a collection of traces from a campus network measurement on YouTube traffic, consisting of trace data related to user requests for specific YouTube content, such as request content, response time, request node, and response node. In this paper, the data we use for simulations includes 200 requests, 96 clients, 113 servers, and 174 contents. To ensure the authenticity of the simulations, the clients and the servers are configured on the network topology correspondingly and proportionally in experiments according to the real network. For the configuration of requests, clients and servers are deployed on routers in network topology randomly, and the relationship among clients, servers and, contents is established based on real requests in YouTube.

Furthermore, our mechanism is compared with two the-state-of-the-art cache allocation algorithms, namely based on centrality cache allocation Method (Centrality-measures based algorithm, CMBA) [17] and Greedy Caching Strategy (Greedy Caching Strategy, GCS) [20] respectively. For comparison simulations, algorithms are implemented under different constraints of cache capacity, in terms of hit ratio, energy consumption, time latency, and throughput.

The parameter settings involved in the simulations are shown in Table 1.

| Parameter                  | Setting |
|----------------------------|---------|
| Simulation time            | 5 times |
| $N$ in Algorithm 1         | 800     |
| $I_{\text{max}}$ in Algorithm 1 | 120    |
| $P_i$ in equation (5)      | 1000W   |
| $\varphi$ in equation (5)  | $1 \times 10^{-7}$ J/bit |
| $\omega$ in equation (7)   | 0.6     |
| $\gamma$ in equation (7)   | 0.4     |
| $\theta$ in equation (10)  | 0.02    |
| $Q$ in equation (11)       | 100     |
| $\sigma$ in equation (12)  | 1       |
| $\alpha$ in equation (13)  | 1       |
| $\beta$ in equation (13)   | 1       |

The parameters in table 1 have specifically described in corresponding equations in this paper, where simulation time is determined according to times of different cache space for different simulations. $N$ and $I_{\text{max}}$ in algorithms are adopted according to the scale of network and ant colony. $P_i$ and $\varphi$ are according to real networks. $\omega$ and $\gamma$ are set according to the importance of time latency, hit ratio, energy consumption, and throughput for network performance. $\theta$, $Q$, and $\sigma$ are determined by experiments to ensure a good result. $\alpha$ and $\beta$ are determined according to the importance of pheromone concentration and heuristic information for the transferring probability of ants.

### B. SIMULATION RESULTS

In order to verify the effectiveness and efficiency of the proposed mechanism, simulations of ACCM are conducted on AttMpls and TW Telecom topologies respectively. To simulate the network, the configuration of nodes in the network topology is given as follows. The nodes in the network are sorted from left to right and from top to bottom. Simulations assume that the size of each request content is 10MB, and the maximum total network cache space is 3GB. For AttMpls topology, the maximum cache capacity of each router is 150MB. For TW Telecom topology, the maximum cache capacity of each router is 100MB. Then, the ant colony inspired cache allocation mechanism is simulated on the configured network topologies. The ant colony is mapped into network topologies respectively, and the ant colony foraging behavior is used to simulate the process of cache allocation. In the process of ant colony foraging, ants search for the path according to pheromone concentration corresponding to the network performance in ICN. And ants tend to choose the path with better network performance and release higher pheromone concentration on the path at the same time. So as the ant colony iterates, the path with the best network performance accumulates the highest pheromone concentration, and the ant colony converges to the path with
the best network performance. The convergence processes of the proposed mechanism on two network topologies are shown in Fig. 4 and Fig. 5 respectively, where network performance is obtained by a normalization method. And the best cache allocation solutions on two network topologies are as follows:

$$C = \{150, 80, 30, 150, 140, 100, 150, 150, 130, 100, 110, 80, 150, 100, 110, 110, 130, 120, 50, 110, 150\} \text{ (MB)}.$$

The cache capacity allocation solution on TW Telecom topology is:

$$C = \{20, 0, 70, 30, 100, 100, 20, 10, 0, 70, 60, 100, 100, 90, 50, 0, 0, 30, 0, 70, 0, 50, 0, 0, 100, 40, 30, 0, 30, 0, 30, 100, 40, 40, 90, 50, 0, 0, 90, 70, 0, 80, 50, 90, 100, 0, 0, 70, 0, 100, 0, 80, 10, 0, 40, 90, 10, 50, 100, 0, 90, 60, 50, 0, 0, 10, 0, 70, 0, 70, 90, 0, 20\} \text{ (MB)}.$$

The convergence process of the mechanism on AttMpls is shown in Fig. 4.

**FIGURE 4.** The convergence process of the mechanism on AttMpls.

**FIGURE 5.** The convergence process of the mechanism on TW Telecom.

C. EVALUATION INDICATORS

In comparison simulations, we construct an evaluation model to compare the performance of algorithms, considering hit ratio, energy consumption, time latency, and throughput as metrics. And the evaluation model is defined according to the evaluation model of network performance described in section III and is expressed as:

$$\begin{align*}
T_{\text{total}} & = \sum_{i=1}^{n} t_{i} c_{i} \\
E_{\text{total}} & = \sum_{i=1}^{n} e_{c_{i}} c_{i} \\
H_{\text{total}} & = \sum_{i=1}^{n} h_{r_{i}} c_{i} \\
T_{\text{P total}} & = \sum_{i=1}^{n} t_{p_{i}} c_{i}
\end{align*}$$

where $T_{\text{total}}$, $E_{\text{total}}$, $H_{\text{total}}$ and $T_{\text{P total}}$ has been showed in section III. And lower $T_{\text{total}}$ and $E_{\text{total}}$, and higher $H_{\text{total}}$ and $T_{\text{P total}}$ are required for a good cache allocation scheme.

D. COMPARISON ANALYSIS

Comparison simulations are conducted on energy consumption, hit ratio, time latency, and throughput in terms of different constraints of cache size, where $C_{\text{max}}$ is set to 150 MB, 200 MB, 250 MB, 300 MB, and 350 MB respectively. And we analyze the results of comparison simulations.

1) ENERGY CONSUMPTION

Energy consumption is calculated by formula (6). The comparison simulations on energy consumption among ACCM, CMBA, and GCS are implemented on AttMpls and TW Telecom topologies respectively under different cache size constraints of each router, and comparison simulation results are shown in Fig. 6 and Fig. 7. It can be seen from figures that under different constraints of cache size, the energy consumption of ACCM is always the lowest, followed by GCS, and CMBA at last. As the cache size increases, caching energy consumption on routers increases, and transmitting energy consumption from request client to server decreases. But increasing caching energy is far more than decreasing transmitting energy, so overall energy consumption increases with cache size increasing.

**FIGURE 6.** Comparisons on energy consumption among ACCM, CMBA, and GCS on AttMpls in terms of different cache size constraints of each router.

2) HIT RATIO

Hit ratio is calculated by formula (7). The comparison simulations on hit ratio among ACCM, CMBA, and GCS are
implemented on AttMpls and TW Telecom topologies respectively under different cache size constraints of each router, and comparison simulation results are shown in Fig. 8 and Fig. 9. It can be seen from the figures that under different constraints of cache size, the hit ratio of ACCM is always the highest, followed by GCS, and CMBA at last. As the cache size increases, routers can cache more diverse contents to respond to requests, and more requests hit contents successfully at content routers. Therefore, the hit ratio of three algorithms increases gradually.

3) TIME LATENCY
Time latency is calculated by formula (5). Comparison simulations on time latency among ACCM, CMBA, and GCS are implemented on AttMpls and TW Telecom topologies respectively under different constraints of cache size, and comparison simulation results are shown in Fig. 10 and Fig. 11.

As shown in the figures, under different cache size constraints of each router, the time latency of ACCM is always the...
lowest, followed by GCS, and CMBA at last. As the cache size increases, more diverse contents can be cached at the router, and processing data time increases, but transmitting time decreases. However, decreasing transmitting time is far more than increasing processing time, so overall time latency decreases with cache size increasing.

4) THROUGHPUT
Throughput is calculated by formula (8). Comparison simulations on throughput among ACCM, CMBA, and GCS are implemented on AttMpls and TW Telecom topologies respectively under different constraints of cache size, and comparison simulation results are shown in Fig. 12 and Fig. 13. As shown in figures, under different cache size constraints of each router, the throughput of ACCM is always the highest, followed by GCS, and CMBA at last. As the cache size increases, routers can cache more contents to respond to requests, and time latency decreases, which has been demonstrated in the last section. Therefore, more data can be transmitted in unit time, and throughput increases.

E. DISCUSSION
From the above simulation results, both in AttMpls and TW Telecom topologies, ACCM proposed in this paper works best in terms of energy consumption, hit ratio, time latency, and throughput compared with CMBA and GCS, which shows the performance of the proposed mechanism is not affected by the structure of the network, such as density. In addition, with the hit ratio increasing, the missing hit ratio decreases, and more requests hit contents at content routers, which reduces energy consumption and time of transmission between users and servers. So, with the hit ratio increasing, the missing hit ratio decreases, which leads to time latency and energy consumption decreasing, and throughput increasing.

The reasons why the proposed mechanism has advantages in energy consumption, hit ratio, time latency, and throughput are analyzed as follows. 1) We construct an evaluation model of network performance in terms of energy consumption, hit ratio, time latency, and throughput. 2) We propose an ant inspired cache allocation mechanism for heterogeneous ICN to allocate cache capacity to each router heuristically. And our theoretical analysis shows that the proposed mechanism can converge to the cache allocation solution with the best network performance.

Therefore, it can be considered that, compared with CMBA and GCS, ACCM works best in cache allocation for heterogeneous information centric network.

VI. CONCLUSION
In this paper, we propose an ant colony inspired cache allocation mechanism to address the cache allocation problem for heterogeneous ICN. First, the evaluation model of network performance is established related to hit ratio, energy consumption, time latency, and throughput. Then, based on the performance evaluation model, we devise a cache allocation mechanism inspired by the ant colony, where an ant colony is mapped into ICN topology and the ant colony foraging behavior is used to simulate the process of cache capacity allocation. And we conduct a theoretical analysis to show that the proposed mechanism can obtain the best cache allocation scheme for ICN. Finally, simulations are driven by real datasets in YouTube and conducted on AttMpls and TW Telecom topologies. Compared with CMBA and GCS in terms of energy consumption, hit ratio, time latency, and throughput, simulation results show that the proposed mechanism works best in cache allocation for heterogeneous ICN. However, there are some limits in this paper. The proposed mechanism allocates cache capacity to routers to optimize network performance for static user requests, but it cannot address dynamic requests in ICN. In the future work, we will focus on the problem of dynamic changes in network requests.

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