Energy Efficiency of Cloud Processors for Small Cell Networks

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Abstract— **A cloud-based networks offered as new wireless architecture, where optimization of radio resources at the base station (BS) is moved to a cloud data center for optimization. In this paper, we propose to minimize the energy consumption at the data center where multiple cloud processors are used for the optimization. As the cell size and networks become respectively smaller and denser, the number of BS to be optimized grows exponentially, resulting in high computational complexity and latency at cloud processors. The computation for the schemes is distributed across multiple processors and done in parallel using belief propagation (BP) method, leading to very low latency with increasing number of BS. Simulation results show that the network energy efficiency performances at the cloud are close to an exhaustive search solution in finding the best configuration.**

Index Terms— **Belief Propagation; Cloud; Parallel Processing; Power Control; Small Cell Networks.**

I. Introduction

Cloud-Based Radio Access Network (C-RAN) for small cell networks have emerged as a promising solution to improve wireless network energy significantly [1]. In these cloud-based networks, multiple physical base stations (BSs) consists only of radio frequency units and simple processing modules. Computation of radio resource allocation and inter-cell interference management move to a cloud for centralized optimization. By centralizing the optimization of radio resources for all small cells, optimal dynamic radio resource management over many cells can be achieved, leading to significantly higher energy efficiency.

The centralized optimization is performed by using multiple processors available at a cloud data center [2]. Multiple processors will significantly reduce the latency and the computational burden of a single processor as the computation can be distributed and performed simultaneously in parallel. In a conventional cloud structure, each base station (BS) is exclusively allocated to a single processor unit in the cloud data center. In other words, the numbers of processors and BSs in the network are equal. An optimization technique to share the computational resources of the processors in the cloud data center across multiple BSs when the numbers of processors are not equal with the number of deployed BSs is proposed in [3]. This feature allows to minimize the number of used processors and improve the data center energy efficiency. In the Long-Term Evolution Advanced (LTEA) standard and many published papers [4], the allocation of cloud processors and BS powers are done separately, leading to inefficient resource utilization. Thus, posing challenges for delivering low latency internet-of-things (IoT) applications in C-RANs. To date, there has been no research that investigates a joint allocation of power and cloud processors.

Recently, a distributed computation technique based on belief propagation (BP) method that allows the BSs cooperation and transmits power computation to be done in parallel to increase network spectral efficiency and to reduce latency, was proposed in [5], [6]. With the BP method, the overall network optimization function that maximizes the spectral efficiency [5], [6] is first decomposed into multiple optimization functions, solvable in parallel at the BSs level. The BSs cooperation then occurs via message exchange between the BSs. The message contains information about the marginal probability distribution of the objective function for network energy efficiency.

The main contributions of this paper are as follows. First, the purpose of this paper is to develop a distributed power optimization that optimizes the network energy efficiency. The develop network energy optimization is expected applicable for both conventional and new cloud structures where either each BS is allocated a dedicated cloud processor or each cloud processor is shared by multiple BSs, respectively. Second, unlike BP scheme in [5], [6] that consider an unconstrained network optimization problem, we consider the received signal-to-interference-plus-noise ratio (SINRs) as the optimization constraints. In [5], [6], all messages, coming from adjacent variable nodes at time *t*, regardless whether the SINR constraint is satisfied or not, are included in the factor node computation. We offer a sum-product algorithm and a message passing formulation that consider the optimization constraints in their sum-product message computations. The developed network energy optimization is based on the BP concept. It is executed in parallel across multiple cloud processors to reduce the latency in cloud-optimization techniques which are critical for new IoT applications. The latencies for the proposed schemes in fact do not change when we increase the number of BSs, as it will be shown later in the paper. Third, we develop a new scalable BP algorithm, where each factor node is connected to only two variable nodes regardless of the number of adjacent interfering BSs in the network. This paper also aimed to have very low latency, as the latency no longer depends on the number of BSs. Unlike the existing BP schemes, [5], [6] the proposed schemes do not allow a BS to transmit to users if a minimum received SINR is not satisfied. This eliminates waste of BS transmission, which happens when the received signal is below the minimum received SINR. The simulation results also show that the network energy efficiency and latency performances of the two proposed algorithms outperform similar schemes in the open literature [6]; and the network energy efficiency are very close to the optimal exhaustive search solution.

II. SYSTEM MODEL AND OPTIMIZATION FORMULATION

In this section, we propose a parallel optimization to allocate BS transmit power in C-RAN for small cell networks to address the above-mentioned problems. In C-RAN, the power allocation optimization for BSs is done in the cloud processors. We consider a downlink transmission for a C-RAN with N BSs. Each BS is assumed to transmit by using the same spectrum for its downlink transmissions. The BSs are connected to the cloud via high-speed optical fiber cables. The computation of radio resources for each BS moves to the cloud. We consider the cloud processors are shared by multiple BSs, we could improve the energy consumption at the cloud data center by minimizing the number of used processors [9]. The resource computation is done in parallel across multiple cloud processors. We assume users are randomly located and connected to the closest BS.

We let user j be the closest user to BS $j \in N$, such that $N=\{1,2,...,N\}$. We further define the set of adjacent BSs to BS j, as $N_j = \{i\ j | i \in N\}$.The transmit power for BS j is denoted as q_j and selected from W possible transmit power values $q_j \in W_j, W_j = \{q_{jw} | w = 1,...,W\}$. The wireless channel between BS j and user k is modelled as $g_{jk} = h_{jk} F(h_{jk}, \beta)$. h_{jk} and $F(d_{jk}, \beta)$ represent the wireless channel coefficient that depends on the distance d_{jk} between BS j and user k and path loss exponent β. The received signal at user j is given as

$$y_j = \sqrt{q_j} g_{jj} + \sum_{k \in N_j} \sqrt{q_k} g_{jk} x_k + z_j g_{jk} \tag{1}$$

where x_j is the symbol transmitted by BS j to user j, drawn from M-ary Quadrature Amplitude Modulation symbols with a symbol energy E[$|x_j|^2$]=1 and $z_j = N(0, \sigma^2)$ represents the additive white Gaussian noise. By using (1), the received SINR at user j, is given as

$$\gamma_j(\mathbf{q}) = \frac{|g_{jj}|^2 q_j}{\sigma^2 + \sum_{k \in N, k \neq j} |g_{jk}|^2 q_k} \tag{2}$$

To ensure the transmissions to all users in N cells satisfy the minimum quality of service, we develop an indicator function for BS j, where BS j transmits only if the received SINR at user j is above the minimum SINR required to deliver the service, Γ_j. An indicator function for each BS j, $I_j(\mathbf{q})$, that computes the energy efficiency at the cloud data center, is defined as the ratio between the transmission rate and the number of processors needed to support the transmissions of BS j, where $\mathbf{q}=\{q_j \cup q_k\}$ is the overall transmit power state of the system such that $j,k \in N$ and $j \neq k$. We let $\eta_j(\mathbf{q})$ represents the portion of cloud processors for processing BS j transmission and defined as

$$\eta_j(\mathbf{q}) = \frac{\varsigma + \kappa \log_2(1 + \gamma_j(\mathbf{q}))}{s} \tag{3}$$

where ς, κ and s represent the overhead for the required instructions for setting up the cloud processor, the relationship between cloud processor instructions and $\gamma_j(\mathbf{q})$, and the amount of instructions that can be executed by a single cloud processor per channel transmission, respectively. We use κ and ς that are estimated by using data logs of real-world traffic in a wireless cellular network across 21 cell sites in a dense cellular network as an input to the hardware experiments in [3], [10].

We define an indicator function, $I_j(\mathbf{q})$ that calculates the network energy efficiency per channel transmission for BS j for j=1,2,...,N. This function has $\mathbf{q}$ as its variables and is defined as

$$I_j(\mathbf{q}) = \begin{cases} \log_2(1+\gamma_j)/\eta_j(\mathbf{q}), & \gamma_j(\mathbf{q}) \geq \Gamma_j, \\ 0, & \gamma_j(\mathbf{q}) = 0, \\ -\infty & \text{otherwise} \end{cases} \tag{4}$$

where the numerator of (4) is the number of cloud processing instructions related to the transmission rate of BS j in a single channel, if BS power allocations $\mathbf{q}$ used. The maximization for the average values of the network energy efficiency at the cloud data centre for N BSs with q_j, j =1,...,N as variables, can be written as

$$\begin{array}{cc} \max\limits_{q_1,...,q_N} & \frac{1}{N} \sum\limits_{j \in N} I_j(\mathbf{q}) \\ \text{subject to} & q_j \in W_j,\ j \in N. \end{array} \tag{5}$$

Here, once the q_j is obtained from (5), we compute the total number of used cloud processors, η, as

$$\eta = \left\lceil \sum_{j \in N} \eta_j(\mathbf{q}) \right\rceil \tag{6}$$

where $\lceil \upsilon \rceil$ denotes an integer round up operation for υ. Note that the global optimal solution for (5) can be obtained by exhaustively searching all possible transmit power combinations for all BSs and selecting the one that gives the maximum of (5). However, although this approach is optimal, it requires a very high computational complexity.

III. CLOUD BASED NETWORK ENERGY EFFICIENCY

In this section, we propose a distributed power optimization algorithm for solving (5) in a parallel manner. We have derived an optimization function that minimizes the energy consumption at the cloud data center when each cloud processor is shared by multiple BSs, subject to the received SINR requirements of the users with the BSs transmit power as variables. We then propose a scalable BP algorithm with low latency, by assuming that the interference component in each of the modified SINR constraints comes only from a single adjacent BS.

A. Parallel Network Energy Efficiency

We first write the probability distribution function (pdf) representations for (5) following [11] that results in a maximum network energy value given by

$$\lim_{\mu \to \infty} E\left[\sum_{j \in N} \mu I_j(\mathbf{q}) \right] = \arg\max_{q_1,...,q_N} \sum_{j \in N} \mu I_j(\mathbf{q}) \tag{7}$$

Next, we decompose (7) into multiple power optimization problems. Thus, the decomposed network energy functions with transmit powers as their variables can be computed in parallel across multiple cloud processors.

Algorithm 1 Parallel Network Energy Efficiency (BPEE)

Input: User j, $j \in N$;
Output: Required transmit power for BS j
Initialize all messages
i.e. $m^{0}_{a\to j}(q_j)=[\mathbf{0}]\ \forall\ a,j\in N$
Set iteration index $t=0$.
Increase t
if $t < t_{\mathrm{MAX}}$, **then**
for each BS j, **do**
Compute $\forall\, a\in N$
$n^{t}_{j\to a}(q_j)=c(t\text{-}1)\sum_{b\in N, b\neq a} m^{t}_{b\to j}(q_j)$
Compute $\forall\, a\in N$
$m^{t}_{j\to a}(q_a)=\sum_{j\in N}\mu I_j(\mathbf{q})+\sum_{b\in N, b\neq a} m^{t}_{b\to j}(q_j)$
Compute $\forall\, a\in N$, $\tilde{m}^{t}_{a\to j}(q_j)=m^{t}_{a\to j}(q_j) \Big/ \underbrace{\sum_{j\in N}\sum_{a\in N}\sum_{q_a\in W_a}\left(m^{t}_{j\to a}(q_a)\right)^2}_{1/c(t)}$
end for
end if
Find the transmit power for BS j using
$\max_{q_j\in W_j}\,[\sum_{a\in N}\tilde{m}^{t}_{a\to j}(q_j)]$

Algorithm 2 Low Latency Parallel Network Energy Efficiency (BPLowEE)

Input: User j, $j \in N$;
Output: Required transmit power for BS j
Initialize all messages
i.e. $m^{0}_{(j,k)\to i}(q_i)=[\mathbf{0}]\ \forall\ j\in N,\ k\in N_j, i\in\{j,k\}$
Set iteration index $t=0$.
Increase t
if $t < t_{\mathrm{MAX}}$, **then**
for each BS j, **do**
Compute $\forall\ k\in N_j$,
$n^{t}_{j\to(j,k)}(q_j)=c'(t\text{-}1)\sum_{a'\in N_i, a\neq(j,k)} m^{t}_{a'\to j}(q_j)$
Compute $\forall\ j\in N,\ k\in N_j, i\in\{j,k\}$,
$m^{t}_{(jk)\to i}(q_i)=\sum_{\mathbf{q}\setminus q_i}\mu I_{jk}(q_j,q_k)+\sum_{l\neq i} m^{t}_{l\to(j,k)}(q_l)$
Compute $\forall\ k\in N_j$, $\tilde{m}^{t}_{(j,k)\to j}(q_j)=m^{t}_{(j,k)\to j}(q_j) \Big/ \underbrace{\sum_{j\in N}\sum_{k\in N_j}\sum_{i\in\{j,k\}}\sum_{q_i\in W}\left(m^{t}_{(j,k)\to j}(q_i)\right)^2}_{1/c'(t)}$
end for
end if
Select the transmit power for BS j using
$b_j(q_j)=\max_{q_j\in W_j}\,[\sum_{j\in N}\sum_{k\in N_j}\tilde{m}^{t}_{(j,k)\to j}(q_j)]$

A factor graph representation of the decomposed optimization problems, based on the concept described in [7] is then developed. The factor graph describes the relationship between the network energy objectives, $I_j(\mathbf{q})$ and transmit power, q_j represented by factor nodes j and variable nodes j, respectively for each BS j. Each cloud processor has a single factor node and a single variable node and cooperates with other cloud processors by exchanging messages containing the marginal distribution estimates of the network energy functions.

A BP method based on the sum-product approach [8], is used over the factor graph that enables cloud processors to cooperate by exchanging the estimates of the marginal distribution of (5) and to optimize a network energy functions in parallel. Each cloud processor computes the marginal estimate of energy efficiency at data center functions in parallel and exchanges the estimates with other cloud processors. The process is repeated until the message values at each cloud processor no longer change.

We denote $n^{t}_{j\to a}(q_j)$ and $m^{t}_{a\to j}(q_j)$ as the messages sent from/to the variable node j to/by the factor node a at iteration t, respectively, for any $j,a\in N$ such that $q_j\in W_j$. Each cloud processor then computes the estimates of the energy efficiency functions for each possible transmit power at BS j. The transmit power that yields the maximum estimate is then used by BS j. The complete optimization process of the proposed parallel power control performed by multiple cloud processors in a cloud. The process is repeated in parallel until the number of iterations hits its maximum, defined t_{MAX}. The complete algorithm for BP based parallel network energy efficiency, referred to as BPEE scheme, is summarized in **Algorithm 1**. Furthermore, the convergence of (7) has been proven mathematically in [11].

B. *Low Latency Parallel Network Energy Efficiency*

We also propose a simplified BP algorithm, namely a BPLowEE scheme as summarized in **Algorithm 2**. The SINR constraints in (3), $\gamma_j(\mathbf{q})\geq\Gamma_j$ and the optimization objective for each BS are decomposed into multiple linear constraints. We assume that the interference component in each of these new constraints comes only from a single adjacent BS and we denote each BS j constraints as $\gamma_{jk}(q_j,q_k)$ for $k\in N_j$. The original SINR constraint in (2) can be expressed as

$$\gamma_{jk}(q_j,q_k)=\frac{\left|g_{jj}\right|^2 q_j\,\dfrac{\left|g_{kj}\right|^2}{\sum_{k\in N_j}\left|g_{kj}\right|^2}}{\sigma^2\,\dfrac{\left|g_{kj}\right|^2}{\sum_{k\in N_j}\left|g_{kj}\right|^2}+\sum_{k\in N,k\neq j}\left|g_{jk}\right|^2 q_k}. \qquad (8)$$

Now, we redefine the indicator function $I_{jk}(q_j,q_k)$, computed by using new $N-1$ SINR definitions in (8) for each BS j, $\gamma_{jk}(q_j,q_k)$, as $I_j(\mathbf{q})=\sum_{k\in N_j} I_{jk}(q_j,q_k)$. If cloud processors are shared by multiple BSs, the indicator function for the energy efficiency at the data center will depend on the transmission rate that in turn depends on $\gamma_{jk}(q_j,q_k)$. By following the same approach above for deriving (7), we can express

$$\lim_{\mu\to\infty}\mathrm{E}\left[\sum_{j\in N}\sum_{k\in N_j}\mu I_{jk}(q_j,q_k)\right]=\arg\max_{q_1,\dots,q_N}\sum_{j\in N}\mu I_j(\mathbf{q}) \qquad (9)$$

that depends only on two variables q_j and q_k. To compute (9) we use a similar BP approach as described above. We let $i \in \{j, k\}$ and $N_i \backslash (j,k)$ denote all the adjacent nodes in the network to node i except for factor node (j,k), respectively. The message to/from factor node (j,k) from/to variable node j at iteration t is now denoted as $m^t_{(jk)\rightarrow i}(q_i)$ and $n^t_{j\rightarrow(j,k)}(q_j)$, respectively. The process above is repeated in parallel for all cloud processors until $t = t_{MAX}$. The transmit power for each cloud processor j is selected as shown in **Algorithm 2**.

IV. LATENCY COMPARISON

In this section, we compare the latency of BPEE and BPLowEE with the non-cooperative scheme in [4] and other power allocation schemes based on a BP approach in [6] and an optimal exhaustive search method. The latency is defined as the average number of iterations needed to converge and the delay due to BS computational processing in each iteration. The iteration delay for BPEE and BPLowEE and the iterative schemes in [4] and [6] are denoted as $t_{MAX,BPEE}$, $t_{MAX,BPLowEE}$, $t_{MAX,NC}$, and $t_{MAX,BPA}$, respectively. We assume that the time needed to compute one possible combination of transmit powers, $\mathbf{q}_j = \{q_i \in W_i \ \forall \ i \in N_j\}$ in one iteration is the same for BPEE, BPLowEE, [4] and [6]. Thus, the delay in each iteration depends on the number of possible combinations of $\mathbf{q}_j$ that need to be searched.

When the scheme in [4] is used, the global network energy optimization problem is decomposed and solved at each cloud processor, allocated exclusively for one BS. The energy optimization is then done in a serial manner where each cloud processor takes a turn in updating its transmit power decision and interference information. When BP approach for the scheme in [6] and the proposed BPEE and BPLowEE are used, cloud processors updates its decisions on BS resource allocation in a parallel manner. As a result, the delay due to the BSs computational processing in each iteration is reduced by N times. Yet, as the number of BSs in the network energy increases, the latency will grow exponentially. When BPLowEE is used, each factor node is connected only to two rather than N variable nodes as in the scheme [6] and BPI. Therefore, the latency per iteration used in BPLowEE is further reduced by W^{N-3} times as compared to [6] and BPEE.

V. SIMULATION RESULTS AND DISCUSSION

In this section, we compare the latency of BPEE and BPLowEE for energy efficiency performance relative to the schemes in [4] and [6] and with the exhaustive search-based schemes. In the simulations, we consider a two-dimensional urban macrocell model from the LTEA standards [12], where 9 BSs are positioned on a 3×3 rectangular grid, operating at frequency 2.14GHz. The parameters used in the paper are summarized in Table 1. All results are evaluated over 500 independent trials.

Figure 1 shows the average latency for $t_{MAX,BPEE}$, $t_{MAX,BPLowEE}$, $t_{MAX,NC}$ and $t_{MAX,BPA}$. As the number of BSs increases, $t_{MAX,NC}$ increase exponentially with the number of BSs. On the other hand, regardless of the network objectives, the average $t_{MAX,BPEE}$, $t_{MAX,BPLowEE}$ and $t_{MAX,BPA}$ remains at 4, 6 and 7 iterations, respectively, as the number of BSs increases. The proposed BPLowEE scheme reduces the latency time even further as its latency is 100 times less than the scheme in [6] which has the lowest latency among cooperative schemes. Furthermore, its latency time is also 48 times less than the scheme in [4].

Figure 1 also shows the average latency when energy efficiency at the cloud data center is used as the optimization objective for BPI and BPII schemes, referred to as $t_{MAX,BPEE}$ and $t_{MAX,BPLowEE}$. As their latencies are the same when other optimization objectives are used, we can conclude that the latency of the proposed BP schemes is insensitive to optimization objectives.

Table 1
Simulation Parameters and Value

Symbol	Description	Value
B	System bandwidth	20MHz
r	Cell radius	500m
β	path loss coefficient	3.76
χ	log normal shadowing coefficient	8dB
σ	thermal noise power density	-174dBm/Hz
$q_{j,4}$	4 power levels with maximum power	43dBm
s	Processor speed [3]	2GHz
ς	Constant coefficient of s	7×10^8
κ	Rate varying coefficient of s [3]	35

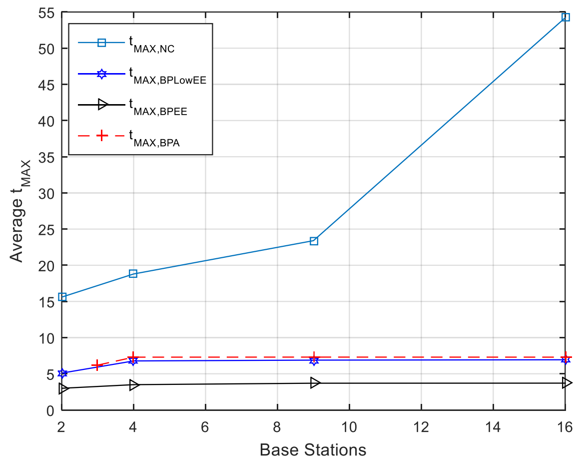

Figure 1: Latency for various methods with Γ_j =5dB and W =4.

Figure 2 shows that the number of used cloud processors for BPEE and BPLowEE schemes with various SINR thresholds can be reduced by 30% over the existing schemes [4] and [6]. We now compare the performance of BPEE and BPLowEE with [4] and [6] and exhaustive search-based schemes in terms of their energy efficiencies of the cloud data center. When compared with the exhaustive search with spectral efficiency as objectives we could see that there is a spectral efficiency degradation of 10% and 13% for BPEE and BPLowEE schemes, respectively.

Note that we cannot guarantee that the BPEE and BPLowEE schemes will converge to the global optimal solution of (5) and (7), respectively. The interdependency in the transmit power decisions between multiple BSs results in a full cycle graph. This leads to a non-optimal transmit power configuration $\mathbf{q}$ as shown in Figure 3 where the two proposed schemes on average are shown to be within 5% (for BPEE scheme) and 10% (for BPLowEE scheme) from an exhaustive search scheme in terms of the energy efficiency at the cloud data center, respectively.

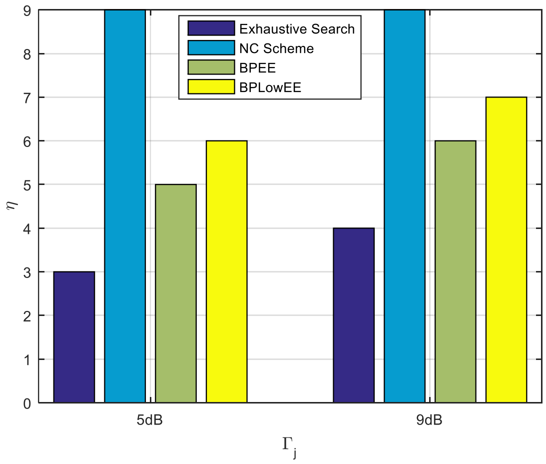

Figure 2: Cloud Processors consumption, η in C-RAN using various methods with Γ_j =5dB and 9dB

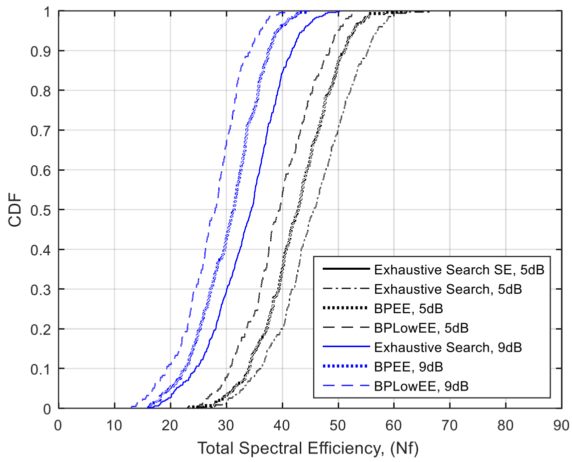

Figure 3: Total spectral efficiency for 9 BSs using various methods with Γ_j = 5dB and 9dB

VI. CONCLUSION

We have proposed a power allocation scheme for C-RAN to maximize the network energy efficiency at the cloud data center and computed in parallel, resulting in low latency. A BP algorithm, based on the sum-product approach is used in the optimization process, where each BS computes a BP belief, that represents the estimate of the network energy functions for each possible BS transmit power. Each BS uses the transmit power given by the maximum estimate of the energy efficiency at the cloud data center. We have also presented a scalable BP algorithm with very low latency. The simulation results show that the proposed schemes significantly outperform other best-known schemes in terms of latency and energy efficiency. The proposed algorithm outperforms the best known existing scheme by at least 15% and 13% in terms of the energy efficiency at the cloud data center.

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