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Social Context-Aware Mobile Data Offloading Algorithm via Small Cell Backhaul Networks

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ABSTRACT In recent years, total mobile traffic has increased explosively, and this has led to severe traffic load on the mobile network operator (MNO)'s core network. Mobile data offloading is a promising solution to alleviate the core network's load. Through such mobile data offloading, MNO can reroute the mobile traffic to other access networks using various radio access technologies, such as WiFi, opportunistic communications, and so on. In addition, social networking traffic has risen sharply due to the popularity of online social networking services, such as Facebook and Twitter. Thus, we need to consider a social context for effective mobile data offloading. In this paper, in order to apply the social context to mobile data offloading, we model the social context in terms of two aspects: the user's social relationships and application's popularity. In addition, we propose a social context-aware mobile data offloading algorithm to maximize the quality of service (QoS) of users in a small cell backhaul offloading environment. The performance evaluation results demonstrate that the proposed algorithm outperforms the other algorithms that do not consider the social context.

INDEX TERMS Mobile data offloading, small cell backhaul networks, social context.

I. INTRODUCTION

Due to the proliferation of smart mobile devices (e.g. smartphones, tablets, etc.), with advanced computing and multimedia capabilities, highly evolved mobile applications have been introduced. These include complicated computations that generate large amounts of traffic which have led to the explosive growth of total mobile traffic. According to Cisco, smart devices accounted for 89 percent of the total mobile data traffic generated despite only accounting for 36 percent of all mobile devices; further, total mobile traffic increased 74 percent [1]. In mobile applications, the use of social networking services (SNSs) such as Facebook and Twitter is increasing sharply, and the corresponding traffic accounts for the second largest contribution to total mobile data traffic, and the use of embedded video (video contents or video links shared by SNS users) in SNSs is growing as well [2]. This considerable traffic from social networking may place a considerable load on the mobile network operator (MNO)'s core network and lead to degradation in the quality of service (QoS) in terms of mobile users. Therefore, studies are necessary to distribute the traffic load considering social context.

Mobile data offloading is one of the most promising solutions to alleviate the traffic load in the MNO's core network. According to Cisco, 51 percent of the total mobile data traffic in 2015 was offloaded onto the fixed network through Wi-Fi or femtocell [1]. Many researchers have studied the offloading schemes based on the various offloading networks, such as WiFi, opportunistic communication, and small cell backhaul networks. In WiFi offloading, the MNO can offload the data to free unlicensed bands. However, from the user's perspective, they may experience poor QoS due to the limitation of the WiFi coverage area [3]. Another approach to mobile data offloading is opportunistic communication. In opportunistic offloading, the MNO might deliver the data to only target users, and then, target users can disseminate the data to other users who can communicate with target users via opportunistic communications. However, this is unreliable for mobile data offloading due to the battery and storage limitation of mobile devices, along with the low incentives for the users of these mobile devices involved in offloading [3].

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The other approach to mobile data offloading is to offload the traffic via small cells, such as femtocells and picocells. In small cell offloading, mobile users can directly route the traffic to the same residential/enterprise network or Internet through small cell backhaul without traversing the mobile core network. 3GPP proposed the local IP access (LIPA) and selected IP traffic offload (SIPTO) for traffic offloading [4]. According to the [5], small cell offloading is effective for the following reasons: the MNO can offload heavy users via small cells (81 percent of data usage occurs mainly indoor) and provide a seamless service to users through an operator-deployed and managed small cell. Thus, in this paper, we focus on the small cell offloading.

As mentioned previously, social networking traffic is increasing, and this exceedingly large traffic is from the repeated downloading of the same popular content [6]. In addition, the popularity of the content is highly affected by the user's social relationships [7]. Thus, applying social contexts to traffic offloading is crucial. Many works exploit social context into offload the traffic and most of these works are even based on opportunistic communications [8]–[10], but the social context is still not yet widely applied to small cell offloading. As mentioned previously, opportunistic communication for mobile data offloading is limited due to several reasons. Therefore, in order to fully exploit social context in mobile data offloading, we propose a mobile data offloading algorithm considering social context based on the small cell offloading, which offloads the data traffic via small cell fixed backhaul networks.

In order to analyze the social context and apply this to the offloading decision, sufficient storage and sophisticated calculation capabilities without high latency are required. Thus, we consider multi-access (or mobile) edge computing (MEC) for mobile data offloading. MEC provides a cloud computing-based IT service environment at the edge of the mobile network that is within the radio access network (RAN) [11]. This can ensure ultra-low latency and high bandwidth, and improve the delivery of service and user quality of experience (QoE). However, the effect of MEC (e.g. low latency, and etc) is beyond the scope of this paper.

The main contributions of this paper include:

- *New Social Context Modeling:* We model the social context to propose the mobile data offloading algorithm, which take advantage of the user's social relationship and the popularity of mobile application services. Through social context modeling, we estimate the probability that each user will select a mobile application service. For convenience, we will shorten 'mobile application services' to 'applications' in this paper.
- *Social Context-Aware Small Cell Mobile Data Offloading Algorithm:* We propose a social context-aware mobile data offloading algorithm to maximize the QoS of small cell users, which is associated with a small cell, in the small cell mobile data offloading. The proposed algorithm determines an offloading weighting factor for each application of each user by estimating the application selection probability and network utilization.
- *Performance Evaluation*: We conduct simulations to demonstrate the good performance of the proposed algorithm, especially in terms of QoS, compared to other algorithms without considering social context modeling.

The remainder of the paper is organized as follows. In Section II, we review the related works. In Section III, we describe the system model including social context modeling. In Section IV, we describe the proposed social context-aware small cell mobile data offloading algorithm in detail. In Section V, we analyze the performance of the proposed algorithm. Finally, we conclude this paper in Section VI.

II. RELATED WORKS

A. MOBILE DATA OFFLOADING

As previously stated, mobile data offloading is a promising solution to alleviate traffic load. Many works have investigated mobile data offloading. In [3], they examined the state-of-the-art works in mobile data offloading in terms of both technologies and business. A few works have been focused on WiFi offloading [12], [13]. In [12], they presented quantitative research into the performance of mobile data offloading via WiFi networks, which indicates that WiFi networks can offload about 65 percent of the total data traffic and achieve about 55 percent battery power saving. In [13], they proposed WiFi offloading mechanisms for vehicular cellular traffic, which is offloaded via carrier-WiFi networks. These mechanisms jointly consider vehicular users' and the MNO's satisfaction as well as the offloading performance.

A few existing works have investigated small cell offloading, such as LIPA/SIPTO [14], [15]. In [14], a bearer-based offloading algorithm was proposed to support a LIPA/SIPTO solution in the MNO's core network, which combines the offloading policy and the bearer information. In [15], they presented the LIPA/SIPTO architectures within a various network environment, discussed the main requirement to support LIPA/SIPTO, and provided a survey on the aspects of management and service continuity in LIPA/SIPTO.

B. SOCIAL CONTEXT IN COMMUNICATIONS

A number of works have examined the social context in communications [16], [17]. In [16], they introduced the basic concepts of socially aware networking (SAN) to exploit the network node's social properties in the design of networking solution and presented a survey of state-of-the-art works in SAN. In [17], they proposed a combined social and communication network model, which can analyze the average delay and success probability under link failure and node mobility properties. In addition, many works have studied the exploitation of social context in communications and networks [18]–[21]. In [18], they provided a survey on state-of-the-art social-aware routing protocols in delay tolerant networks and investigated the design issues of social-aware routing. In [19], they proposed an approach to optimize resource allocation and improve the traffic offloading in device-to-device (D2D) wireless small cell networks, which jointly exploits the wireless and social context of users. In [20], they proposed a framework to improve the quality of recommendations in location-based social networks, which exploits social context as well as spatial and temporal context in a collaborative filtering algorithm.

C. SOCIAL CONTEXT IN MOBILE DATA OFFLOADING

A number of works have considered social context in mobile data offloading [8]–[10], [22]. In [8], they proposed a traffic offloading framework through opportunistic communications in mobile social networks and investigated the strategies to select the appropriate user sets for pushing, which is based on the user's SNS spreading impacts, content access delay, and the mobility patterns. In [9], they proposed a social-aware opportunistic sharing framework assisted by the tags of users and contents; the tags indicate the social similarity between users. This framework chooses an optimal user subset by analyzing the social tags of users and contents. In [10], they proposed a scheme of multiple source selection to find the optimal number of initial source nodes and select the best source node for traffic offloading in mobile social networks, which consider the diffusion time and the data transmission cost. In [22], they proposed two social-aware incentive mechanisms in a WiFi access point (AP) based offloading, which is based on the modeling of social relationships of mobile users by a PageRank-based algorithm.

As shown here, most of offloading algorithms considering social context have been based on opportunistic communications. However, as mentioned in the Introduction, we consider the small cell mobile data offloading using the social context. In this paper, we take into consideration the two aspects of social contexts, such as the user's social relationship and the application's popularity. In addition, we investigate how the social context affects the performance of the mobile data offloading.

III. SYSTEM MODEL

A. NETWORK ARCHITECTURE

We consider a mobile data offloading network architecture as shown in Fig. 1, which consists of a small cell, a MEC server, an MNO's core network, a small cell backhaul network, and multiple mobile device users. We assume that all mobile devices are associated with the small cell and that the small cell type is for residential and enterprise use, which have the wireline backhaul network (e.g. broadband Internet service) and can directly connect the Internet. We assume that the MEC server is located in close proximity to the small cell. The MEC server plays a key role in mobile data offloading, which collects the information to analyze the social context and network utilization, and decides the amount of offloading the mobile traffic for each application of each user. After the offloading decision, the offloading traffic is routed from the MNO's core network to the small cell's backhaul network. In order not to consider a user's mobility in this small cell offloading, we assume that all users are fixed at the same

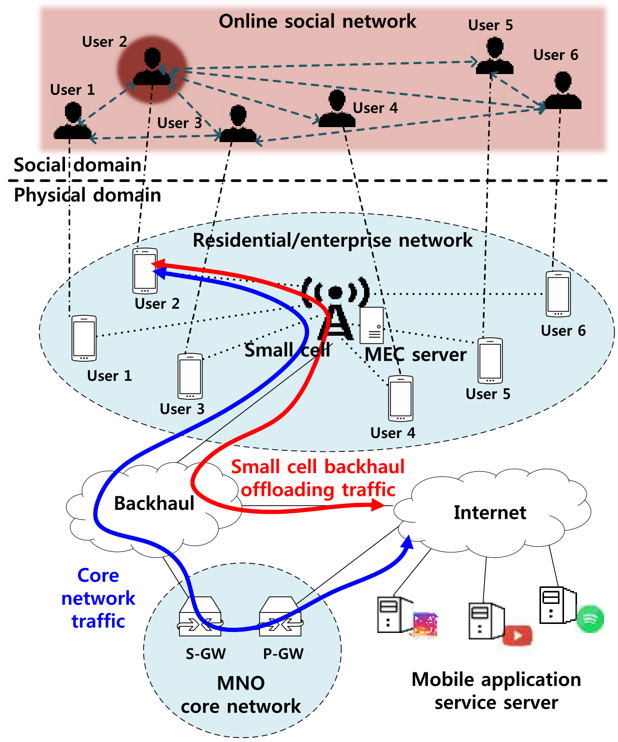

FIGURE 1. The network architecture for mobile data offloading considering social context in a social network.

distance from a small cell. We assume that the users have the social relationships with each other through the online social network activities and that the application's selection behavior is affected by these social relationships.

B. MODELING THE SOCIAL CONTEXT

Based on the [6] and [7], we model the social context using the following attributes:

- *User's Social Impact:* According to [7], the social relationships are one of the primary schemes for which the users find and select applications. In addition, some users with a high social impact have a strong influence on the application popularity. Thus, we assume that a users application selection behavior is affected by its' social ties in a specific social network, i.e., a user's application selection behavior is affected by the selection behavior of other neighbor users, where the neighbor users refer to the users who have some social relationship with a specific user. In addition, we assume that the most popular application of the most socially influential user will be frequently selected.
- *Application's Popularity:* According to [6], the popularity distribution of contents shows power-law with truncated tails, and this means that the most popular applications are frequently selected. Thus, we assume that a user's application selection is affected by the number of times the application is selected.

First, we model social context in terms of each user's social impact. As mentioned previously, we consider a user i,

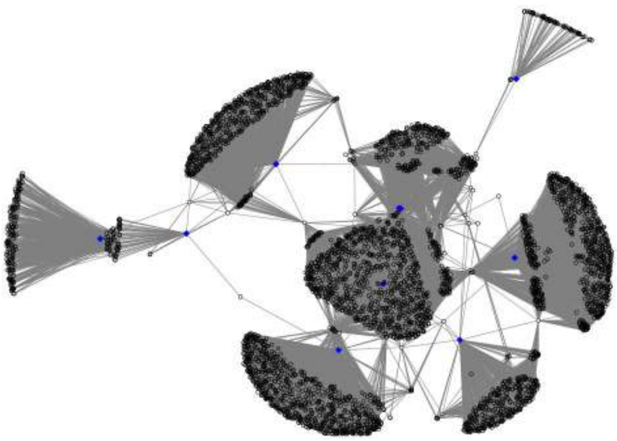

FIGURE 2. The example of a social graph generated by NodeXL.

where $i \in \mathcal{I} = \{1, 2, ..., N\}$. The social relationship in the social network is modeled as a social graph using an undirected graph, in which $G = \{V, E\}$ where V is the set of vertices and E is the set of edges, and edge $(v_i, v_{i'}) \in E$ is identical to the edge $(v_{i'}, v_i) \in E$. Vertex v_i denotes user $i \in \mathcal{I}$ and edge $(v_i, v_{i'})$ denotes a social relationship between user i and user i'. Then, based on the social graph, we construct the social adjacency matrix, $\mathbf{A} = \left[a_{ii'}\right]_{N\times N}$, where N denotes the total number of users, and the entity $a_{ii'}$ in $\mathbf{A}$ indicates that whether user i and user i' have a social relationship or not and it is given by

$$a_{ii'} = \begin{cases} 0, & (v_i, v_{i'}) \notin E, \quad (1a) \\ 1, & (v_i, v_{i'}) \in E. \quad (1b) \end{cases}$$

We use a degree centrality in the social graph as the user's social impact in a social network as follows.

$$DegC_i = \frac{deg(i)}{n-1}, \tag{2}$$

where $deg(i)$ is the number of directly connected neighbors of user i and n is the maximum number of possible connected edges in the social graph [16]. Fig. 2 shows an example of a social graph from the data set of ego-Facebook in SNAP [23], and the social graph is generated by NodeXL [24]. As shown in Fig. 2, the blue diamond and the black circle refer to the users in the social network, and the solid line refers to the social relationship between the users. In particular, the blue diamond means one of the high degree centrality users, i.e. this blue diamond refers to the high social impact user in the social network.

Second, we model the social context in terms of the application's popularity. We consider the case in which a user i selects application j, where $j \in \mathcal{J} = \{1, 2, ..., M\}$. Based on the application's selection frequency, we construct the application selection history matrix, $\mathbf{H} = \left[h_{ij}\right]_{N\times M}$, where M denotes the total number of applications, and the entity h_{ij} refers to the number of times that user i selects the application j. In addition, we calculate the rank of application popularity, r_{ij}, which indicates the rank for application j of user i. When the rank for application j of user i is smallest, this indicates that application j is most popular with user i.

Finally, considering both the user's social impact and application popularity, we define the social impact-aware popularity factor, which is given by

$$SI_{ij} = DegC_i \cdot \frac{1/r_{ij}}{\sqrt{\sum_j (1/r_{ij})^2}}. \tag{3}$$

This means that the highest rank application for the highest social impact user will affect the other user's application selection, and this will apply to the estimation of the application selection probability in the next subsection.

C. ESTIMATION OF SOCIAL CONTEXT-AWARE APPLICATION SELECTION PROBABILITY

In order to estimate the user's application selection probability, we use the Indian buffet process (IBP) model, which is a stochastic process model that defines a probability distribution over binary matrices by specifying a procedure by which customers (objects) choose dishes (features) [25]. Then, in order to apply a user's social impact and application popularity to the estimation of the user's application selection, we define the social context-aware application selection probability based on the social context modeling described in the previous subsection.

First, when a user does not have any social relationships with others, i.e. $a_{ii'} = 0, \forall i' \in \mathcal{I}_i$, where $\mathcal{I}_i$ is the set of users that may have a social relationship with user i, the user i's application j selection probability follows the Poisson distribution and it is given by

$$P_{ij} = SI_{ij} \cdot \left[\frac{(\alpha/i)^{m_0^i}}{m_0^i!} \cdot e^{-\frac{\alpha}{i}}\right], \tag{4}$$

where α is a Poisson distribution parameter and m_0^i is the number of new selected applications by user i. This means that the user is not affected by the other user's selection due to no social relationship.

By contrast, when a user has any social relationships with others, i.e. $a_{ii'} = 1, \forall i' \in \mathcal{I}_i$, the user i's application j selection probability follows the IBP model but is modified by whether or not the application j has previously been selected at least once by user i and this is given by

$$P_{ij} = \begin{cases} SI_{ij} \cdot \left\{\frac{(\alpha/i)^{m_0^i}}{m_0^i!} \cdot e^{-\frac{\alpha}{i}}\right\}, & h_{ij} = 0, \quad (5a) \\ SI_{ij} \cdot \left\{\frac{m_j^{i'}}{i}\right\}, & h_{ij} \geq 1, \quad (5b) \end{cases}$$

where $m_j^{i'}$ is the total sum of the number of selection for application j by other users that have a social relationship with user i and it is defined as

$$m_j^{i'} = \sum_{i'} h_{i'j}, \quad \forall i' \in \mathcal{I}_i. \tag{6}$$

TABLE 1. Notations.

Notations	Explanation
$\mathcal{I}$	Set of users
$\mathcal{J}$	Set of applications
i	User index
j	Application index
N	Number of users
M	Number of applications
$\mathbf{A}$	Social adjacency matrix
$\mathbf{H}$	Application selection history matrix
$a_{ii'}$	Social relationship indicator between user i and i'
h_{ij}	Number of times the user i selects the application j
$DegC_i$	Degree centrality of user i
r_{ij}	Rank of application for application j of user i
SI_{ij}	Social impact-aware popularity factor for application j of user i
$\mathcal{I}_i$	Set of users that have a social relationship with user i
P_{ij}	Social context-aware application selection probability for application j of user i
m_0^i	Number of new selected application by user i
$m_j^{i'}$	Total sum of the number of selection for application j by other users that have a social relationship with user i
w_{ij}	Selected offloading weighting factor for application j of user i
$W_{ij}(u)$	Selectable offloading weighting factors for application j of user i
U_{BN}, U_{CN}	Network utilization of backhaul and core network
C_{BN}, C_{CN}	Network capacity of backhaul and core network
m_j^i	Number of time the user i selects the application j
R_{ij}, D_{ij}, Pe_{ij}	Expecte data rate, transmission delay, and packet error loss rate for application j of user i
R_{BN}^j, R_{CN}^j	Backhaul network and core network supportable data rate for application j
D_{BN}^j, D_{CN}^j	Backhaul network and core network transmission delay for application j
Pe_{BN}^j, Pe_{CN}^j	Backhaul network and core network packet error loss rate for application j
L_j	Average packet size for application j
O	Objective function
$w_{\mathrm{R}}, w_{\mathrm{D}}, w_{\mathrm{Pe}}$	QoS weighting factors for data rate, transmission delay, and packet error loss rate
$w_{ij\max}$	Offloading weighting factor for application j of user i to maximize the QoS
TL_{ij}	Traffic volume for application j of user i
TL_{ij}^{off}	Offloading traffic volume for application j of user i
$\tilde{\mathcal{W}}_{ij}$	Set of the offloading weighting factor values for application j of user i
w_{ij}^k	k^{th} offloading weighting facor value for application j of user i
K	Number of intervals
$R_{ij}^k, D_{ij}^k, Pe_{ij}^k$	The k^{th} expecte data rate, transmission delay, and packet error loss rate for application j of user i
$\tilde{\mathcal{O}}_{ij}$	Set of the objective function values for application j of user i
o_{ij}^k	k^{th} objective function value for application j of user i
$\mathcal{J}_{-j}$	Set of applications except application j
$\tilde{w}_{ij\max}$	Final offloading weighting factor for application j of user i to maximize the QoS

$m_j^{i'}$ is the principal difference from the original IBP model. In the original IBP model, they simply take account of the total number of application selections without considering whether the user really knows the number of application selections for other users.

IV. PROPOSED SOCIAL CONTEXT-AWARE SMALL CELL MOBILE DATA OFFLOADING ALGORITHM

In this section, we propose the social context-aware mobile data offloading algorithm through small cell backhaul networks. The objective of the mobile data offloading algorithm is to determine the offloading weighting factor to maximize the QoS of users and the detailed algorithm is stated in Algorithm 1.

First, we calculate the selectable offloading weighting factors based on (4), (5), and network utilization. These factors enable to offload more traffic for the application with higher social context-aware probability, and to offload more traffic to the backhaul network when the core network utilization is relatively higher than the backhaul network utilization. Based on this, we define the selectable offloading weighting factors $W_{ij}(u)$ as follows.

$$W_{ij}(u) = \frac{P_{ij}}{\sqrt{\sum_j P_{ij}^{\;2}}} \cdot \frac{u}{U_{\mathrm{CN}} + U_{\mathrm{BN}}}, \tag{7}$$

where $u \in [U_{\mathrm{CN}}, U_{\mathrm{CN}} + U_{\mathrm{BN}}]$, and U_{BN} and U_{CN} are the utilization of the backhaul and core network, respectively, as given by

$$U_{\mathrm{BN}} = \frac{\sum_i \sum_j w_{ij} \cdot L_j \cdot m_j^i}{C_{\mathrm{BN}}}, \tag{8}$$

$$U_{\mathrm{CN}} = \frac{\sum_i \sum_j (1 - w_{ij}) \cdot L_j \cdot m_j^i}{C_{\mathrm{CN}}}, \tag{9}$$

where m_j^i is the number of times user i selects application j, and C_{BN} and C_{CN} are the backhaul and core network capacities, respectively.

Next, we calculate the selectable expected QoS values, R_{ij} is the expected data rate, D_{ij} is the expected transmission delay, and Pe_{ij} is the expected packet error loss rate for application j of user i when the offloading weighting factor is w_{ij}, which is selected from $W_{ij}(u)$. These QoS values are given by

$$R_{ij} = w_{ij} R_{\mathrm{BN}}^j + (1 - w_{ij}) R_{\mathrm{CN}}^j, \tag{10}$$

$$D_{ij} = w_{ij} D_{\mathrm{BN}}^j + (1 - w_{ij}) D_{\mathrm{CN}}^j, \tag{11}$$

$$Pe_{ij} = w_{ij} Pe_{\mathrm{BN}}^j + (1 - w_{ij}) Pe_{\mathrm{CN}}^j, \tag{12}$$

where R_{BN}^j and R_{CN}^j are the backhaul network and core network supportable data rate for application j, respectively; this means that the network can actually support data rates in the current network condition, and they are described in detail [26]. D_{BN}^j and D_{CN}^j are the average transmission delay for application j in the backhaul network and core network, respectively, and these are defined as

$$D_{\mathrm{BN}}^j = \frac{L_j}{R_{\mathrm{BN}}^j}, \tag{13}$$

$$D_{\mathrm{CN}}^j = \frac{L_j}{R_{\mathrm{CN}}^j}, \tag{14}$$

Algorithm 1 Social Context-Aware Small Cell Offloading Algorithm

Phase1 Estimate the application selection probability
  Using the social context model, estimate the application selection probability by (4) and (5)
Phase 2 Find the selectable offloading weighting factors
  for $i = 1$ **to** N **do**
    for $j = 1$ **to** M **do**
      Calculate the selectable offloading weighting factors, $W_{ij}(u)$ by (7)
    end for
  end for
Phase 3 Calculate the selectable expected data rate, delay, packet error loss rate
  for $i = 1$ **to** N **do**
    for $j = 1$ **to** M **do**
      Calculate R_{ij}, D_{ij}, Pe_{ij}
    end for
  end for
Phase 4 Determine the maximum offloading weighting factor
  repeat
    Calculate the objective function O and determine the $w_{ij\max}$ value for each application j of each user i from the $W_{ij}(u)$
  until When O is maximum
Phase 5 Calculate the offloading volume
  Calculate the offloading traffic volume for each application of each user, $TL_{ij}^{\text{off}} = w_{ij\max} \cdot TL_{ij}$

where L_j is the average packet size for application j. Pe^j_{BN}, Pe^j_{CN} are the packet error loss rate for application j in the backhaul network and core network, respectively, which vary according to the network utilization.

Next, we define the objective function to maximize the QoS of users and this is defined as

$$O = \sum_i \sum_j \left[w_{\text{R}} \frac{R_{ij}}{\sqrt{\sum_j R_{ij}^2}} + w_{\text{D}} \frac{1/D_{ij}}{\sqrt{\sum_j (1/D_{ij})^2}} + w_{\text{Pe}} \frac{1/Pe_{ij}}{\sqrt{\sum_j (1/Pe_{ij})^2}} \right], \quad (15)$$

where $w_{\text{R}}, w_{\text{D}}$, and w_{Pe} are the QoS weighting factors for data rate, delay and packet error loss rate, respectively, and it depends on each user's QoS parameter preference, which refers to how important each QoS parameter is. Then, we calculate the objective function for each expected QoS value and repeat this until the objective function reaches its maximum. When the objective function is maximum, we finally determine the maximum offloading weighting factor for each application j of user i, $w_{ij\max}$ from the selectable offloading weighting factors to maximize the QoS of total small cell users.

Next, we calculate the offloading ratio for each application of each user, $TL_{ij}^{\text{off}} = w_{ij\max} \cdot TL_{ij}$ and offload the traffic for each application of each user to the backhaul network by TL_{ij}^{off}.

Algorithm 2 Offloading Weighting Factor Search Algorithm

for $i = 1$ **to** N **do**
  for $j = 1$ **to** M **do**
    for $k = 1$ **to** K **do**
      Calculate $w_{ij}^k \in \tilde{\mathcal{W}}_{ij}$
    end for
  end for
end for
for $i = 1$ **to** N **do**
  for $j = 1$ **to** M **do**
    for $k = 1$ **to** K **do**
      Calculate $R_{ij'}^k$, $D_{ij'}^k$, and $Pe_{ij'}^k$
    end for
  end for
end for
for $i = 1$ **to** N **do**
  for $j = 1$ **to** M **do**
    for $k = 1$ **to** K **do**
      Calculate the objective function value o_{ij}^k
    end for
    $\tilde{w}_{ij\max} = \arg\max_{\forall w_{ij}^k \in \tilde{\mathcal{W}}_{ij}} \tilde{\mathcal{O}}_{ij}$
  end for
end for
return $\tilde{\mathcal{W}} = [\tilde{w}_{ij\max}]_{N \times M}$

However, finding the offloading weighting factor to maximize the objective function for all applications of all users is difficult because every possible combination of offloading weighting factors for all applications of all users must be compared heuristically. Thus, we propose the offloading weighting factor search algorithm as given in Algorithm 2. Using this algorithm, we find the offloading weighting factor for a specific application of a specific user. In order to determine this, we compare the objective function values of a specific user when the offloading weighting factor value for the specific application varies whereas the offloading weighting factor values for other applications are fixed.

First, let $\tilde{\mathcal{W}}_{ij} = \{w_{ij}^1, w_{ij}^2, \ldots, w_{ij}^k, \ldots, w_{ij}^K\}$ denote the set of the offloading weighting factor values, where K is the number of intervals, and we calculate the k^{th} offloading weighting factor value for application j of user i as follows.

$$w_{ij}^k = \min(\mathcal{W}_{ij}) + (k-1) \cdot \frac{\max(\mathcal{W}_{ij}) - \min(\mathcal{W}_{ij})}{K}. \quad (16)$$

Next, we calculate the k^{th} expected data rate, delay, and packet error loss rate for application j of user i as follows.

$$R_{ij}^k = w_{ij}^k R_{\text{BN}}^j + (1 - w_{ij}^k) R_{\text{CN}}^j, \quad (17)$$

$$D_{ij}^k = w_{ij}^k D_{\text{BN}}^j + (1 - w_{ij}^k) D_{\text{CN}}^j, \quad (18)$$

$$Pe_{ij}^k = w_{ij}^k Pe_{\text{BN}}^j + (1 - w_{ij}^k) Pe_{\text{CN}}^j. \quad (19)$$

Let $\tilde{\mathcal{O}}_{ij} = \{o_{ij}^1, o_{ij}^2, \ldots, o_{ij}^k, \ldots, o_{ij}^K\}$ is the set of the objective function values for application j of user i, and we define the k^{th} objective function value for application j of user i as follows

$$o_{ij}^{k} = w_{\mathrm{R}} \frac{R_{ij}^{k}}{\sqrt{\sum_{\forall j' \in \mathcal{J}_{-j}} \left(R_{ij'}^{1}\right)^2 + \left(R_{ij}^{k}\right)^2}} + w_{\mathrm{D}} \frac{1/D_{ij}^{k}}{\sqrt{\sum_{\forall j' \in \mathcal{J}_{-j}} \left(1/D_{ij'}^{1}\right)^2 + \left(1/D_{ij}^{k}\right)^2}} + w_{\mathrm{Pe}} \frac{1/Pe_{ij}^{k}}{\sqrt{\sum_{\forall j' \in \mathcal{J}_{-j}} \left(1/Pe_{ij'}^{1}\right)^2 + \left(1/Pe_{ij}^{k}\right)^2}}, \quad (20)$$

where $j' \in \mathcal{J}_{-j}$ refers to one of the applications in the set of applications except application j. o_{ij}^{k} is obtained from the expected QoS values for application j of user i when the offloading weighting factor value for application j is w_{ij}^{k} from $\tilde{\mathcal{W}}_{ij}$ while the offloading weighting factor values for other applications except application j are fixed to w_{ij}^{1}.

Then, we determine the final offloading weighting factor value for application j of user i, $\tilde{w}_{ij\max}$, as follows.

$$\tilde{w}_{ij\max} = \arg\max_{\forall w_{ij}^{k} \in \tilde{\mathcal{W}}_{ij}} \tilde{O}_{ij}. \quad (21)$$

This value means the offloading weighting factor value for the maximum objective function value for application j of user i.

V. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed algorithm through the extensive simulations. We compare the performance of the proposed algorithm with those of two other algorithms: the algorithm using the social context model without considering the user's social impact (without centrality), and the algorithm not using the social context model (without centrality & history). The algorithm without centrality is based on the application selection probability model not using the degree centrality term in social impact-aware popularity factor, and the algorithm without centrality and history is based on the application selection probability model not using the social impact-aware popularity factor.

A. EVALUATION ENVIRONMENT

As mentioned in Section III-A, we assume the small cell mobile data offloading architecture, which consists of users, a small cell, a MEC server, a MNO's core network, and a small cell backhaul network. We set the number of users as $N = 60$ and assume that all users are associated with the small cell. We assume that the backhaul network initially has a slightly bad condition compared to the core network, but this network condition will vary according to network utilization. Based on this assumption, we set the network capacity of the backhaul and the core network as $C_{\mathrm{BN}} = 800$ Mbps and $C_{\mathrm{CN}} = 1300$ Mbps, respectively [27]. In addition, the packet error loss rate is randomly selected from a uniform distribution over $[10^{-3}, 10^{-2}]$ for the backhaul network and a uniform distribution over $[10^{-4}, 10^{-3}]$ for the core network [28] and they vary according to network utilization. We set the number of applications as $M = 100$, and the traffic of each application is generated into four classes as determined by [29], with the details shown in Table 2. We assume that this packet error loss rate varies according to the network utilization. We use the ego-Facebook data set from Stanford Large Network Dataset Collection as the social network, in which Facebook is one of the most popular online social networking services [23]. As provided in [30], we first perform the IBP for 10,000 rounds with 100 applications. Then, based on the social context modeling, each user selects applications from 100 applications.

TABLE 2. Traffic for each application parameters.

Parameter	Data Rate	Ratio
Web	Uniform(150,449) kbps	36%
Music/Audio	Uniform(450,749) kbps	8%
SD Video	Uniform(750,1149) kbps	20%
HD Video	Uniform(1150,2300) kbps	36%

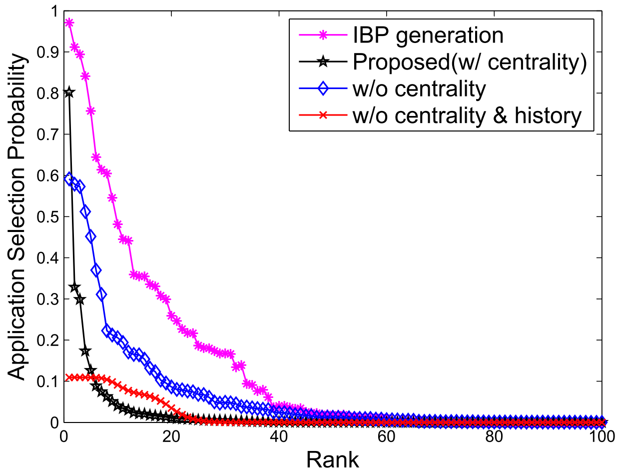

FIGURE 3. Application selection probability vs rank.

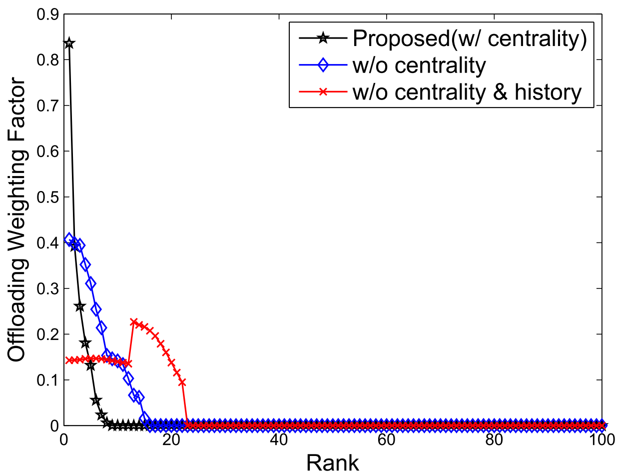

FIGURE 4. Offloading weighting factor vs rank.

B. APPLICATION SELECTION PROBABILITY

Figs. 3, 4 show the estimated application selection probability and the offloading weighting factor based on the application's rank. In Fig. 3, we compare the application selection probability of the proposed model with those of the other two models to the IBP-generated data, because the IBP model is verified by [30], which is similar to real data. We observe that the curve of the model without centrality shows the most similar tendency to that of the IBP curve, but the curve of the proposed model is similar to the IBP curve on the whole. In particular, when the application's popularity rank is high, the probability value of the proposed model is most similar to the value of IBP. In addition, as shown in Fig. 4, the curve of the proposed algorithm and the algorithm without centrality show a similar tendency to that of the curve in Fig. 3. Furthermore, we observe that the proposed algorithm determines the offloading weighting factor to be a higher value as the rank of application is higher. However, the curve of the algorithm without centrality and history does not show a similar tendency to the curve of Fig. 3 because this algorithm does not use the social context model to determine the offloading weighting factor. From Fig. 3, 4, we can observe that due to the social context modeling from two aspects, the proposed algorithm can estimate the application selection probability similar to the real data and determine the offloading weighting factor of high-rank application to be higher.

C. INFLUENCE OF SOCIAL CONTEXT

In this subsection, we set the QoS weighting factors to the same values as $w_{\mathrm{R}} = 0.33$, $w_{\mathrm{D}} = 0.33$, and $w_{\mathrm{Pe}} = 0.33$ so as to only investigate the influence of social context.

Fig. 5 shows the expected QoS value according to the number of iterations, which are averaged by all users and applications. We observe that the proposed algorithm outperforms the other algorithms in terms of data rate and transmission delay. In data rate, the performance of the proposed algorithm is improved by about 28.6 percent compared to the value of the algorithm without centrality and history, and in transmission delay, the performance of the proposed algorithm is improved by about 37.5 percent compared to that of the algorithm without centrality. This indicates that the proposed algorithm can determine the appropriate offloading weighting factor for each application of each user due to the two aspects of social context modeling, which improves the performance of data rate and delay much more and leads to an enhanced total QoS of the user. However, in terms of packet error loss rate, the performance of the proposed algorithm is degraded by about 6 percent. Since we assume a bad backhaul network condition compared to that of the core network, especially in terms of packet error loss rate, the proposed algorithm determines the offloading weighting factor, which results in the enhancement of the user's total QoS despite slight degradation of the packet error loss rate.

In order to demonstrate the QoS performance from another angle, we consider the QoS value according to the rank, which

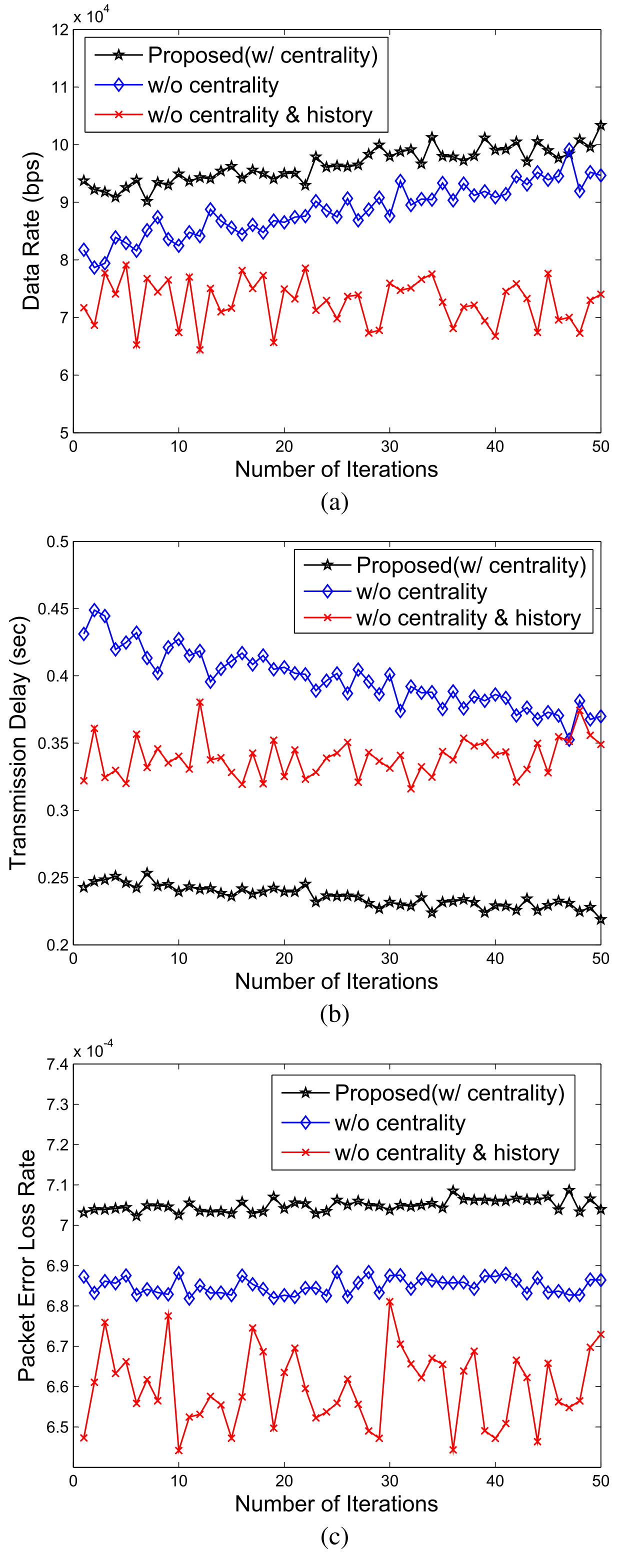

FIGURE 5. **Average expected QoS value vs. iterations (a) data rate (b) transmission delay (c) packet error loss rate.**

is averaged by all users. As shown in Fig. 6, in the proposed algorithm, the QoS value of the high-rank application is much better compared to other algorithms, especially for data rate

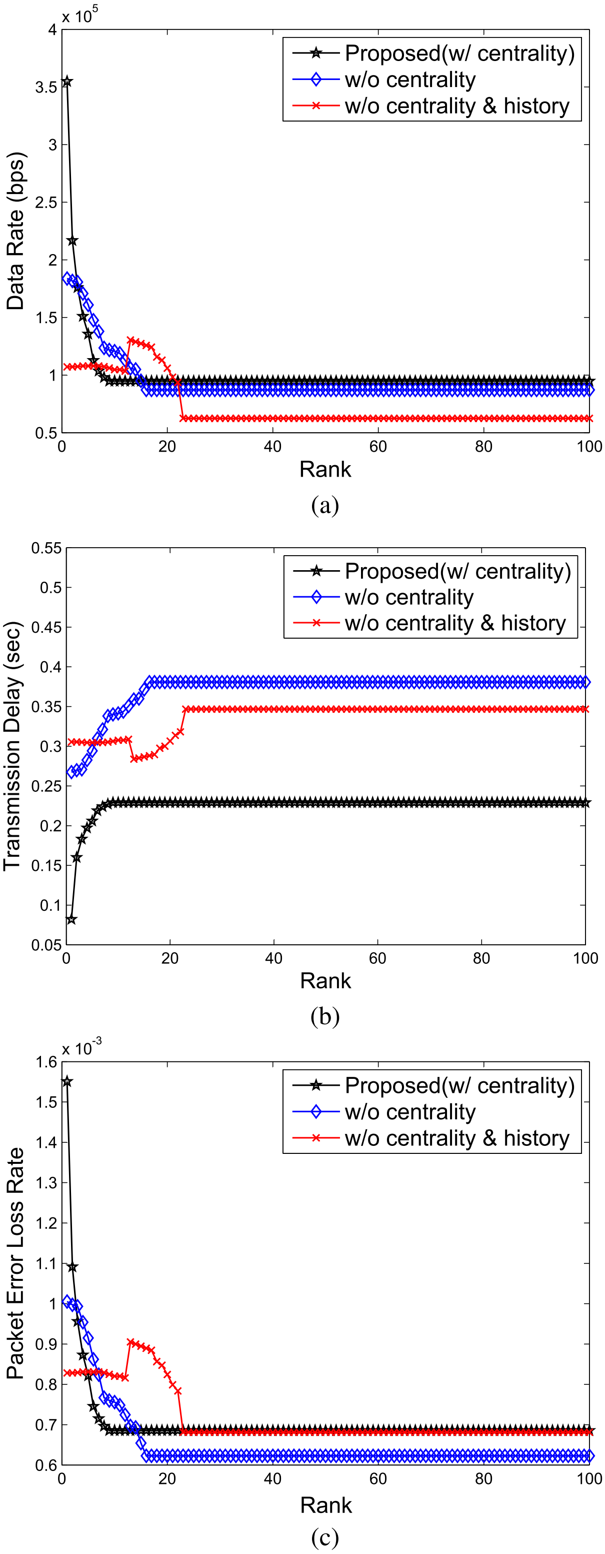

FIGURE 6. Average expected QoS value vs. rank (a) data rate (b) transmission delay (c) packet error loss rate.

and transmission delay. In the proposed algorithm, in order to maximize the total QoS of users, this might set the offloading weighting factors to high values, which is for a few high-rank applications of high social impact users. Otherwise,

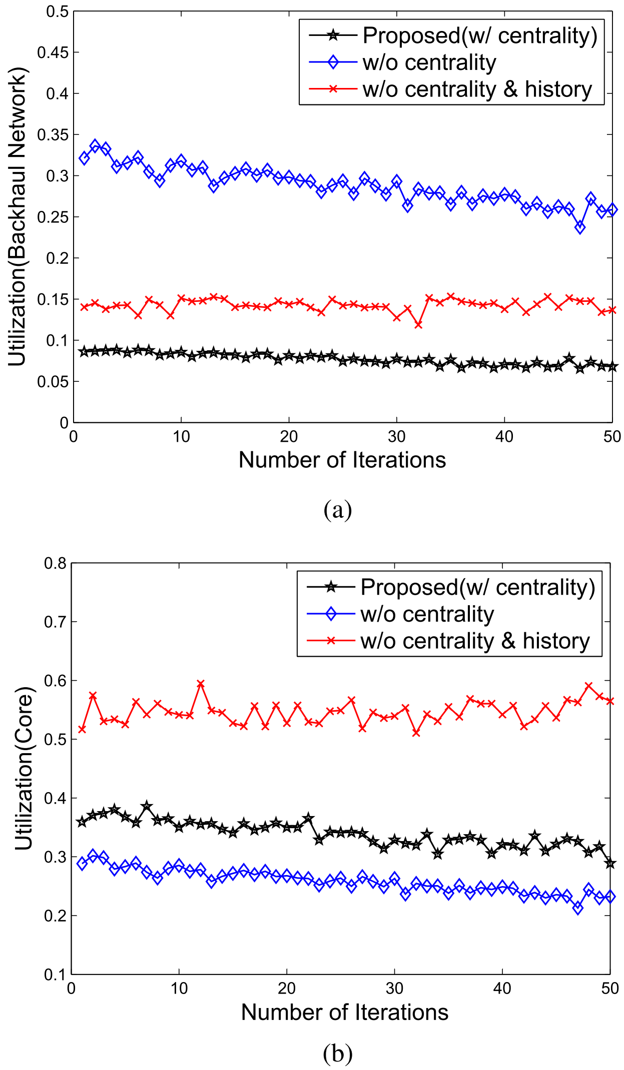

FIGURE 7. Network utilization vs. iterations (a) backhaul network (b) core network.

in the algorithm without centrality and history, the QoS values according to the rank do not show a similar tendency to those of other algorithms, as it shows good performance in data rate and transmission delay, and bad performance in packet error loss rate at the higher rank. Because they do not use the social context modeling, this algorithm is not affected by the rank of application.

Fig. 7 shows the network utilization of the backhaul and core network. The proposed algorithm has the lowest value in the backhaul network and the second lowest value in the core network as shown in Fig. 7. This means that the proposed algorithm can suitably distribute the core network's traffic load as well as maximize the QoS of users although they may not offload a lot of traffic to the backhaul network. Otherwise, in the algorithm without centrality, this can substantially alleviate the core network's traffic load, but result in a slight QoS degradation compared to that of the proposed algorithm. In addition, in the algorithm without centrality and

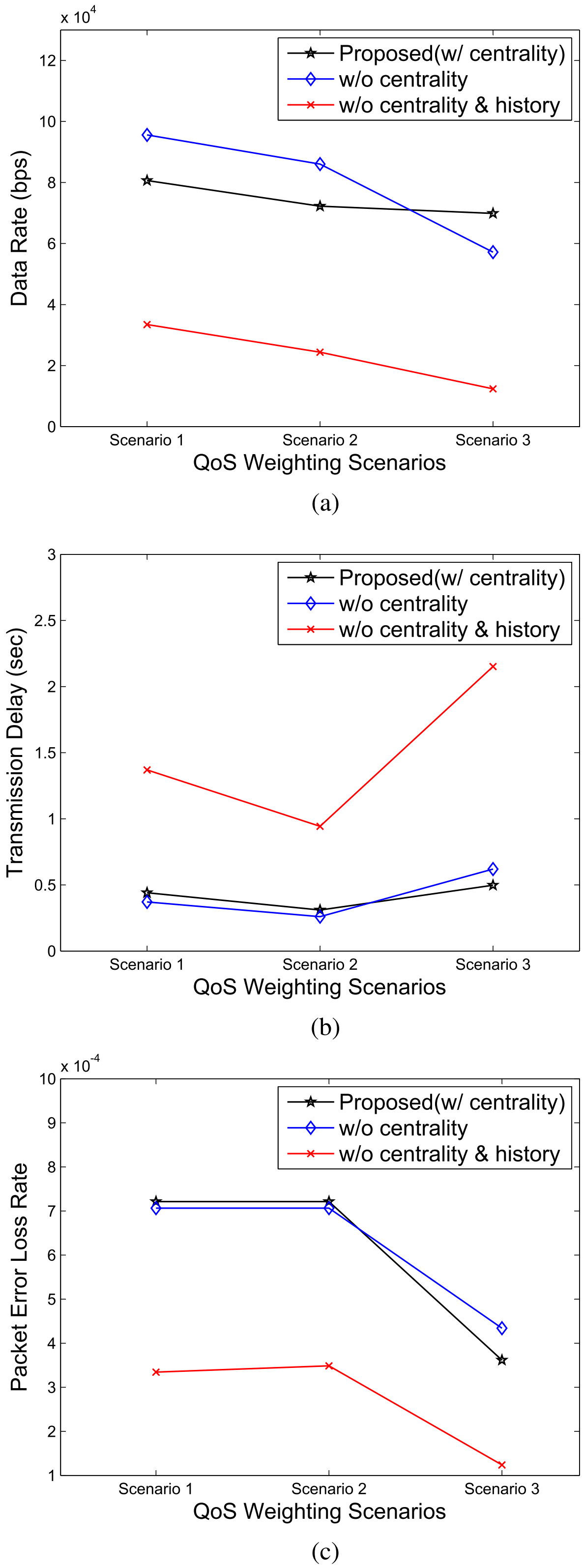

FIGURE 8. Average expected QoS value vs. QoS weighting scenarios (a) data rate (b) transmission delay (c) packet error loss rate.

history, this algorithm does not have any advantages in terms of alleviating the core network load and enhancing the QoS of users.

From Figs. 5– 7, it can be observed that the QoS of users may not be improved substantially, although the traffic of the high popularity application is offloaded much more. In addition, for the effective mobile data offloading, it should take account of not only the application's popularity but also the user's social impact based on the user's social relationship in the same way as the proposed algorithm.

D. INFLUENCE OF QOS WEIGHTING FACTOR

In this subsection, we consider three QoS weighting scenarios: scenario 1 for high data rate weighting ($w_R = 0.8$, $w_D = 0.1$, $w_{Pe} = 0.1$), scenario 2 for high transmission delay weighting ($w_R = 0.1$, $w_D = 0.8$, $w_{Pe} = 0.1$), and scenario 3 for high packet error loss rate weighting ($w_R = 0.1$, $w_D = 0.1$, $w_{Pe} = 0.8$). According to these QoS weighting scenarios, Fig. 8 depicts the average expected QoS value. From Fig. 8, it can be observed that the QoS weighting scenarios have the least effect on the proposed algorithm due to exploiting the two aspects of social context modeling, and they have the largest effect on the algorithm without centrality and history due to the lack of consideration of social context.

VI. CONCLUSION

In this paper, we have proposed the social context-aware mobile data offloading algorithm via small cell backhaul networks to maximize the QoS of small cell users. We model the social context from two perspectives, the user's social relationships and the application's popularity, and estimate the social context-aware application selection probability. Based on this, we proposed the social context-aware mobile data offloading algorithm. The results of the performance evaluation demonstrate that the proposed algorithm outperforms the other algorithms without considering social context, especially in terms of data rate and transmission delay. In addition, the simulation results show that the proposed algorithm can appropriately alleviate the core network's traffic load and maximize the QoS of users, despite offloading less traffic to the backhaul network.

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