IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received May 21, 2016, accepted June 1, 2016, date of publication June 14, 2016, date of current version July 7, 2016.

*Digital Object Identifier 10.1109/ACCESS.2016.2580615*

# Location-Recommendation-Aware Virtual Network Embedding in Energy-Efficient Optical-Wireless Hybrid Networks Supporting 5G Models

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This work was supported in part by National Natural Science Foundation of China under Grant 61302070, Grant 61401082, Grant 61471109, and Grant 61502075, in part by the Fundamental Research Funds for the Central Universities under Grant N130817002, Grant N140405005, and Grant DUT15RC(3)009, in part by the Foundation of the Education Department of Liaoning Province under Grant L2014089, in part by the China Post-Doctoral Science Foundation Project under Grant 2015M580224, in part by the Liaoning Province Doctor Startup Fund under Grant 201501166, and in part by the State Key Laboratory for Novel Software Technology, within the Nanjing University under Grant KFKT2015B12.

**ABSTRACT** Given the possibility of ubiquitous 5G wireless access, location data bridge the gap between the physical world and digital online social networking services and also reflect user preferences and even interdependence among users. Owing to this interdependence, the advertiser can push corresponding products to users according to location recommendations, i.e., advertisement targeting. To achieve this mobile cloud computing service, after moving the computing capacity away from end devices to data centres (DCs), the converged infrastructure integrating optical metro and ubiquitous wireless access technologies is proposed in accordance with the 5G model. To minimize energy consumption, we propose a novel design framework of location-recommendation-aware virtual network embedding. This design framework determines the interdependency among user groups so that we can embed the virtual networks owned by user groups with a high interdependence into the same DC of the substrate optical-wireless hybrid infrastructure. Thus, the adviser can locally push the corresponding products to user groups at a single DC instead of consuming a large amount of energy to build inter-DC paths. The simulation results show that our design framework has greater energy efficiency and more profitable advertisement targeting compared with the benchmark, and the result of our heuristic is very close to the upper bound.

**INDEX TERMS** 5G-based location recommendations, energy efficiency, optical-wireless integration, virtual network embedding, problem transformation, bound analysis.

## I. INTRODUCTION

Given the possibility of ubiquitous 5G wireless access, location data tend to bridge the gap between the physical world and digital online social networking services; as a result, new correlations of users will be created [1]–[4]. Location data may be travel trajectories or location-tagged media content such as photos and videos, as in Fig. 1(a). In particular, users record their route connecting point locations to convey basic information such as distance, visiting duration, velocity, and even experiences along a particular travel trajectory. Thus, a deeper understanding of user preferences is enabled based on location data because users' location histories contain a rich set of information that reflects their preferences. Moreover, the interdependency among users can also be determined because two persons may co-occur in the same point location or share similar location histories. Owing

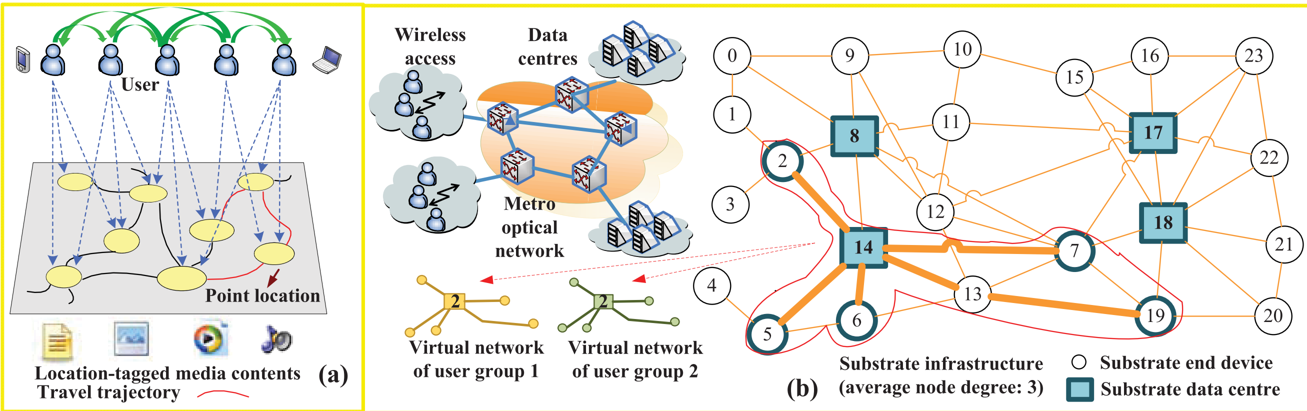


**FIGURE 1.** (a) User-location graph; (b) Location-recommendation-aware virtual network embedding.

to this interdependency, the recommendation of a stand-alone location (a Point of Interest or POI) or sequential POIs along a travel trajectory (a POI trajectory) becomes popular, and the advertiser can push the corresponding products to users according to location recommendations, i.e., *advertisement targeting* [5]–[7].

As a new and emerging application, advertisement targeting requires an efficient process and analysis of location; in addition, the concept of mobile cloud computing, where computing capacity is moving away from the end user to Data Centers (DCs), has been introduced. Obviously, advertisement targeting has become a classic mobile cloud computing service, and the small-scale DC located close to the end devices of users enables a deeper understanding of user preferences. To collect location histories of users, communication among the small-scale DC and users should be achieved; then, the requirement to interconnect users with DCs introduces the additional need for a 5G wireless network that is seamlessly integrated with the optical DC infrastructure [8]–[10].

Figure 1(b) shows a converged infrastructure integrating optical metro and ubiquitous wireless access technologies in accordance with the 5G model. In this converged network environment, management and control information will be exchanged across multiple domains (e.g., BaseBand processing Units, BBUs), causing increased service setup costs and state convergence latencies. Fortunately, the concept of infrastructure virtualization can be utilized to create network slices (virtual networks). Every user group has its own virtual network that will be embedded into a part of the substrate infrastructure. For example, the virtual networks of user groups 1 and 2 are shown in the lower-left side of Fig. 1(b). In each virtual network, the rectangle denotes the virtual node to be mapped into a certain small-scale DC in the substrate infrastructure, and its internal number represents the computing resources required to understand user preferences; the remaining circles are virtual nodes to be mapped into the end devices of users, and the virtual link between the rectangle and a circle represents the communication bandwidth. As in Fig. 1(b), these two virtual networks are embedded into the same DC of the substrate infrastructure under the principle of minimizing the energy consumption for advertisement targeting.

In this paper, for a certain user group, we first propose novel recommendation methodologies of a stand-alone POI and even a POI trajectory. Next, the interdependency (similar recommended POI trajectories) among user groups will be determined so that we can embed the virtual networks owned by the user groups with a high interdependency into the same DC of the substrate infrastructure. As a result, we can locally push as many corresponding products as possible to user groups at a single DC instead of consuming a large amount of energy to build inter-DC paths. On the basis of this, we design a new location-recommendation-aware virtual network embedding heuristic for energy-efficient optical-wireless hybrid networks supporting the 5G model. We also discover that the aforementioned problem of minimizing energy consumption is equivalent to maximizing the profitability of advertisement targeting, and the corresponding upper bound is analyzed to demonstrate the effectiveness of our approach. The main contributions are summarized as follows.

- This paper is the first work to focus on the location-recommendation-aware virtual network embedding in energy-efficient optical-wireless hybrid networks supporting 5G models.
- We have made an NP-hard problem transformation from minimizing energy consumption to maximizing the profitability of advertisement targeting; the goal is to determine the optimal solution, i.e., the upper bound of profitability, in theory. The result of our heuristic has been close to this upper bound, with a converging ratio of 97%.
- Extensive simulation results are shown. In particular, compared to traditional virtual network embedding without the awareness of location recommendations, the improvement ratios of profitability and energy efficiency are 20% and 38%, respectively.

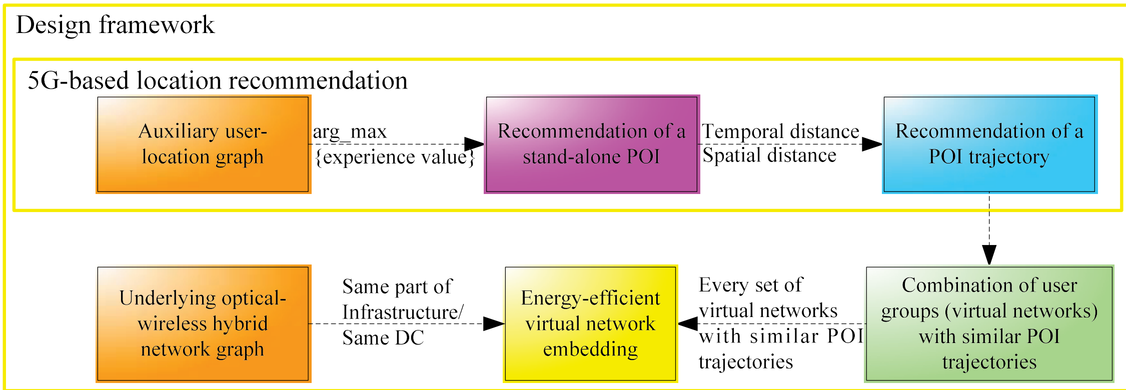


**FIGURE 2.** Our design framework.

The rest of this document is structured as follows. Section II provides a general overview of our design framework. In Section III, we give a detailed description of our problem, including the formulation of the mathematical problem, proof of NP-hardness, the problem transformation and analysis of the upper bound. In Section IV, we propose heuristics to solve our problem with a low time complexity. The simulation results for evaluating the performance of our approach are given in Section V. We summarize the related works in Section VI. Finally, in Section VII, we conclude this paper.

## II. DESIGN FRAMEWORK

A general description of our design framework, which manly includes 5G-based location recommendation and energy-efficient virtual network embedding, is shown in Fig. 2. First, we select the POI with the highest experience value as the recommendation of the stand-alone POI for each user group according to the information reflected in the auxiliary user-location graph, as illustrated in Fig. 1(a). This information includes the friendships among users in one group and the mapping relationship between users and POIs. Next, the POI trajectory including sequential POIs in ascending order of timestamp will be recommended for each user group if that POI trajectory has acceptable temporal and spatial distances. Finally, followed by the energy-efficient virtual network embedding heuristic, we put the virtual networks of the user groups with similar POI trajectories together into a set, and embed the virtual networks from the set into the same DC of the optical-wireless hybrid network graph, as illustrated in Fig. 1(b).

Why is our heuristic energy efficient? As shown in Fig. 3, if the traditional virtual network embedding without the awareness of location recommendations is invoked, the two virtual networks are embedded into different DCs of the substrate infrastructure even though they have similar POI trajectories. Then, the path between DCs 17 and 14 must be found before the advertiser pushes the corresponding products to user groups, thus leading to energy consumption to establish

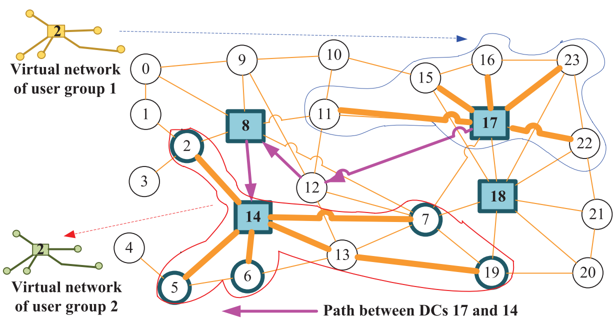


**FIGURE 3.** Traditional virtual network embedding without the awareness of location recommendations.

the inter-DC path. However, as demonstrated in Fig. 1(b), the virtual networks owned by those two user groups will be embedded into the same DC once they have similar POI trajectories; then, the energy consumption for the inter-DC path establishment will be mitigated because the adviser can locally push the corresponding products at a single DC. Furthermore, the larger the number of virtual networks with similar POI trajectories embedded into the same DC, the higher the level of energy savings that is achieved.

## III. PROBLEM DEFINITIONS AND ANALYSIS

In this section, we first introduce the 5G-based location recommendation model and optical-wireless hybrid network model, and some key notations are also presented. We then formulate our problem, discuss its NP-hardness and make an effective transformation for it to find the upper bound.

### A. 5G-BASED LOCATION RECOMMENDATION MODEL

We further construct an auxiliary user-location graph for each user group in Fig. 4. Both 5G users and POIs are represented by vertices. There are three kinds of links in this graph: 1) friendship links among users in one group; 2) the links between users and POIs created by users; 3) the links among POIs. In general, this graph can be denoted as $G(V, E)$, where $V = \{v_1, v_2, \ldots, v_m, v_{m+1}, \ldots, v_{m+n}\}$ and $e_{i,j} = (v_i \rightarrow v_j) \in E$ if $v_i$ is linked to $v_j$ $(1 \leq i, j \leq m+n)$. Note that $n$ is

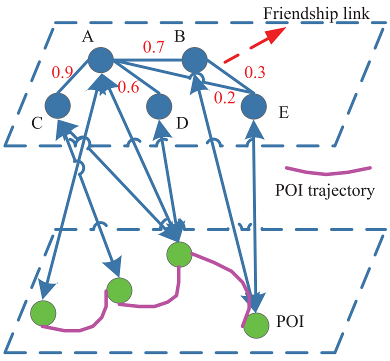


**FIGURE 4.** Auxiliary user-location graph for one user group.

the total number of POIs, while $m$ is the total number of users in one group. Each POI $POI_k \in \{v_{m+1}, \ldots, v_{m+n}\}$ has four-dimensional information including an experience value functioning as an important criterion for recommendations, POI name, POI location and visiting duration.

### B. OPTICAL-WIRELESS HYBRID NETWORK MODEL

We describe the converged infrastructure integrating optical metro and ubiquitous wireless access technologies in the form of the graph $G_s(V_s, D_s, E_s)$, where $V_s$ is the set of end devices and $D_s$ is the set of small-scale DCs, each with an initial computing-resource capacity $C_{DC}$. Every link of the set $E_s$ has enough initial communication bandwidth, and the entire system will process $N_{ug}$ virtual networks (i.e., there are a total of $N_{ug}$ user groups). In the virtual network $G^k_{vn}(V^k_{vn}, E^k_{vn}, c, ba)$ of the $k^{th}$ user group, the number of virtual nodes to be mapped into end devices is determined by the average node degree of the substrate infrastructure, i.e., $N^{vn}_{ed} = |V^k_{vn} - 1| = ranf(2, \lceil |E_s|/(|V_s| + |D_s|) \rceil)$. Here, $ranf(a, b)$ returns a random integer between $a$ and $b$. In other words, each user group will have $N^{vn}_{ed}$ users. In addition, $c$ denotes the computing resource required to understand preferences of users in the same group, and $ba$ is the communication bandwidth between two virtual nodes.

### C. NOTATION DEFINITIONS

To facilitate discussion, we list important notations below.

- $C_{DC}$: Initial computing-resource capacity of each DC.
- $N_{ug}$: Total number of virtual networks (user groups) that will be processed by the entire system.
- $N^{vn}_{ed}$: Number of virtual nodes to be mapped into end devices, for each virtual network, i.e., the total number of users in one group.
- $c$: Computing resource required to understand preferences of users in the same group.
- $ba$: Communication bandwidth between virtual nodes.
- $\alpha_l$: Energy consumed by in-line amplifiers on the link $l \in E_s$.
- $\beta^{l,w}_{i,j}$: is 1 if the link $l$ is used by the path with consuming wavelength $w$ from DC $i$ to DC $j$; it is 0 otherwise.
- $W$: Set of wavelengths.
- $\gamma^s$: Energy consumed for wavelength switching.
- $c^l_{i,j}$: Number of paths from DC $i$ to DC $j$ on the link $l \in E_s$.
- $h_{v,s,k}$: is 1 if the virtual node $v \in V^k_{vn}$ is mapped onto the substrate node $s \in V_s \cup D_s$; it is 0 otherwise.
- $Pay$: Relevant fees paid if the advertisement has been recommended for a user group.

### D. PROBLEM FORMULATION

With the model and assumptions, we investigate the following problem: How to implement the location-recommendation-aware virtual network embedding for energy-efficient optical-wireless hybrid networks supporting 5G models, such that 1) the POI trajectory can be effectively recommended for each user group; 2) the following energy consumption of inter-DC path establishments can be minimized.

$$Minimize\ E = \sum_{l \in E_s} \sum_{i,j \in D_s : i \neq j} \sum_{w \in W} \alpha_l \cdot \beta^{l,w}_{i,j} + \sum_{l \in E_s} \sum_{i,j \in D_s : i \neq j, src(l) \neq i,j} \gamma^s \cdot c^l_{i,j} \quad (1)$$

In Eq. (1), the first item defines the total energy consumed by the in-line amplifiers on all links, while the second item gives the total energy consumed by the optical switches for the wavelength switching of all paths. To formulate the problem, the above objective shall satisfy a number of constraints.

$$\sum_{s \in V_s \cup D_s} h_{v,s,k} = 1, \quad \forall v \in V^k_{vn};\ \forall k \in [1, N_{ug}] \quad (2)$$

$$\sum_{v \in V^k_{vn}} h_{v,s,k} \leq 1, \quad \forall s \in V_s \cup D_s;\ \forall k \in [1, N_{ug}] \quad (3)$$

$$\sum_{k=1}^{N_{ug}} \sum_{v \in V^k_{vn}} h_{v,s,k} \leq C_{DC}, \quad \forall s \in D_s \quad (4)$$

$$\sum_{l \in L^{out}_s} c^l_{i,j} - \sum_{l \in L^{in}_s} c^l_{i,j} = 0, \quad \forall i, j \in D_s : i \neq j; \quad \forall s \in (V_s \cup D_s - \{i, j\}) \quad (5)$$

$$c^l_{i,j} = \sum_{w \in W} \beta^{l,w}_{i,j}, \quad \forall l \in E_s;\ \forall i, j \in D_s : i \neq j \quad (6)$$

$$\sum_{\forall i,j \in D_s : i \neq j} \beta^{l,w}_{i,j} \leq 1, \quad \forall l \in E_s;\ \forall w \in W \quad (7)$$

$$\sum_{l \in L^{out}_s} \beta^{l,w}_{i,j} - \sum_{l \in L^{in}_s} \beta^{l,w}_{i,j} = 0, \quad \forall i, j \in D_s : i \neq j; \quad \forall s \in (V_s \cup D_s - \{i, j\});\quad \forall w \in W \quad (8)$$

Equations (2) and (3) both guarantee that a virtual node is mapped onto only one substrate node. Equation (4) is the capacity constraint of each substrate DC node. Constraint (5) ensures that the amount of outgoing paths must be equal to the amount of incoming ones at each intermediate substrate node.

Equations (6) and (7) both guarantee that, on the link traversed by a path, there is only one wavelength assigned to this path. Equation (8) ensures that, for each path, the number of wavelengths used for the incoming and outgoing paths are the same at each intermediate substrate node.

### E. PROBLEM ANALYSIS

First, we demonstrate the NP-hardness of the aforementioned problem using the following proposition.

*Proposition 1:* Our problem is NP-hard.

*Proof:* The authors in [8]–[10] have highlighted the traditional virtual network embedding without the awareness of location recommendations is a NP-hard problem. In addition to the constraints (listed in Eqs. (2)-(8)) necessary for virtual network embedding, the POI trajectory recommendation also needs to be solved for our problem. In other words, our problem is at least as hard as traditional virtual network embedding. Therefore, our problem is NP-hard.

*Proposition 2:* The aforementioned problem of minimizing energy consumption is equivalent to maximizing the profitability of advertisement targeting.

*Proof:* As mentioned in section II, the more virtual networks with similar POI trajectories that are embedded into a single DC, the higher the level of energy savings. Coincidentally, the larger the number of user groups at a single DC to which a POI trajectory is locally recommended, the higher the profitability. Therefore, the aforementioned problem of minimizing energy consumption is equivalent to maximizing the profitability of advertisement targeting. Note that, within each DC, only when the number of successfully embedded virtual networks with similar POI trajectories exceeds a threshold $T$, will the corresponding profitability be earned. This constraint is rational because it is impossible for the adviser to recommend a POI trajectory for a few user groups at a high expenditure.

*Proposition 3:* The upper bound of our problem, i.e., the maximal profitability, is $Pay \cdot [(|D_s| \cdot C_{DC})/c]$.

*Proof:* The maximal total number of successfully embedded virtual networks will be obtained by assuming that all DCs are replaced by one large DC with aggregated computing resources, i.e., $(|D_s| \cdot C_{DC})/c$. Then, without considering the constraint of the threshold $T$, the maximal profitability is $Pay \cdot [(|D_s| \cdot C_{DC})/c]$, which will demonstrate the optimality of our design framework.

## IV. HEURISTICS

As mentioned in subsection III.D, there are two sub-problems that are required to be solved: 1) the POI trajectory can be effectively recommended for each user group; 2) the energy consumption of inter-DC path establishments can be minimized. Correspondingly, for a certain user group, we first propose novel recommendation methodologies of a stand-alone POI and even a POI trajectory in subsections IV.A and IV.B orderly. Next, in subsection IV.C, to minimize energy consumption, a novel location-recommendation-aware virtual network embedding is designed for optical-wireless hybrid networks supporting 5G models. Finally, the time complexity is given in subsection IV.D. Some important notations used in this section are listed as follows.

- $as$: Experience value (authority score) of a POI.
- $h_{users}$: Hub-score vector, where each dimension is the hub-score of one user who has visited a specified POI.
- $W_{u-POI}$: Link-weight vector, where each dimension is the weight of the link from the user to one of his visited POIs.
- $hs$: Hub score ($hs$) of one user who has visited a specified POI.
- $W_u$: Link-weight vector, where each dimension is the weight of the friendship link between two users.
- $as_{POIs}$: Authority-score vector, where each dimension is the authority-score of the POI visited by a specified user.
- $W_{POI-u}$: Link-weight vector, where each dimension is the weight of the link from one POI to a specified user who has visited this POI.
- $A_i^1$: Friendship vector of the user $U_i$.
- $A_i^2$: Transition vector of the user $U_i$.
- $g(U_i, U_j)$: Social distance between users $U_i$ and $U_j$.
- $deg(i)$: Number of friends owned by the user $U_i$.

### A. RECOMMENDATION METHODOLOGY OF A STAND-ALONE POI

The experience value (authority score $as$) of a POI is determined by the average hub score of the users who have visited this POI, which is in Eq. (9). Here, $0 < \beta < 1$. The hub score ($hs$) of one user who has visited a specified POI is decided by the average hub score of this user's friends who have visited this POI (please see $(1-\beta) \cdot W_u \cdot h_{users}$ in Eq. (10)), the average authority score of POIs visited by this user (pls. see $(1-\beta) \cdot W_{POI-u} \cdot as_{POIs}$ in Eq. (10)), and this user's initial hub score $hs^0$.

$$as = (1-\beta) \cdot W_{u-POI} \cdot h_{users} \tag{9}$$

$$hs = (1-\beta) \cdot [W_u \cdot h_{users} + W_{POI-u} \cdot as_{POIs}] + \beta \cdot hs^0 \tag{10}$$

In Fig. 4, the number beside a friendship link denotes the direct relationship degree between users at two ends of that friendship link. Based on pre-determined direct relationship degrees, we introduce an additional two vectors to enable the creation of $W_u$.

1) Friendship vector $A_i^1$ of the user $U_i$: In Fig. 4, the direct relationship degree between users A and B is 0.7. User B knows C through A, i.e., B and C are not friends now, so the direct relationship degree between users B and C is 0. Correspondingly, if users $U_i$ and $U_j$ are not friends now, the friendship vector element $A_i^1[j] = 0$. Obviously, $A_i^1[i] = 0$.
2) Transition vector $A_i^2$ of the user $U_i$: First, we should know the friendship vector of each user under principle 1). For example, the friendship vector of user B in Fig. 4 is $A_B^1[A] = 0.7$, $A_B^1[B] = 0$, $A_B^1[C] = 0$, $A_B^1[D] = 0$, and $A_B^1[E] = 0.3$; thus,

$A_B^1 = \{0.7, 0, 0, 0, 0.3\}$. Similarly, the friendship vectors of other users are
$A_A^1 = \{0, 0.7, 0.9, 0.6, 0.2\}$,
$A_C^1 = \{0.9, 0, 0, 0, 0\}$,
$A_D^1 = \{0.6, 0, 0, 0, 0\}$,
and $A_E^1 = \{0.2, 0.3, 0, 0, 0\}$.
Then, the transition vector $A_B^2$ of the user B is
$\sum_{k\in\{v_1,v_2,\ldots,v_m\}}(A_B^1[k]\cdot A_k^1) =$
$\{0.06, 0.58, 0.63, 0.42, 0.14\}$.

After these two types of vectors are decided upon, the social distance $g(U_i, U_j)$ between users $U_i$ and $U_j$ is found in Eq. (11). Here, $w_1$ and $w_2$ are weight coefficients, and $w_1 + w_2 = 1$. Because a smaller social distance indicates a deeper friendship, the weight $W_u(i,j)$ of the friendship link between users $U_i$ and $U_j$ is computed according to Eq. (12). Then, the vector $W_u$ can be finally determined. Similarly, the values of $W_{u-POI}$ and $W_{POI-u}$ are found in Eqs. (13) and (14), respectively. Here, $NPOI_k$ records the total number of users who have visited $POI_k$, and $N(U_i)$ records the total number of POIs visited by the user $U_i$.

$$g(U_i, U_j) = \frac{1}{w_1\cdot A_i^1[j] + w_2\cdot A_i^2[j]}, \quad \forall i \tag{11}$$

$$W_u(i,j) = \frac{1}{deg(i)\cdot g(U_i, U_j)}, \quad \forall i \tag{12}$$

$$W_{u-POI} = \frac{1}{NPOI_k}, \quad \forall k \tag{13}$$

$$W_{POI-u} = \frac{1}{N(U_i)}, \quad \forall i \tag{14}$$

Here, the variables $i, j, k$ are only indices of users or POIs. Obviously, the scope of them is between 1 and the maximal number of users or POIs.

For a certain user group, we compute experience values (authority scores) for all possible POIs using Eqs. (9) and (10) and rank these POIs in descending order of the experience value. If only one POI should be recommended for the user group, we merely need to select the top POI with the maximal experience value.

### B. RECOMMENDATION METHODOLOGY OF A POI TRAJECTORY

A POI trajectory includes sequential POIs in the ascending order of timestamp, and every POI along a trajectory is represented as $POI_k = (x_k, y_k, t_k, as_k)$. Here, $as_k$ is the experience value (authority score) determined by Eqs. (9) and (10); $t_k$ is the timestamp; $x_k$ and $y_k$ are the latitude and longitude where $POI_k$ originates, respectively. Thus, if two POIs have a space-time relationship, there will be a link with the weights of the spatial and temporal distances between them. The spatial distance $Dist(POI_i, POI_j)$ is the spherical distance between the locations of two POIs $POI_i$ and $POI_j$, which is found in Eq. (15). The temporal distance $Int(POI_i, POI_j)$ between $POI_i$ and $POI_j$ is the time interval computed by Eq. (16). To avoid a case where multiple POI trajectories are recommended for the same user group, the spatial threshold $\theta_s$ and temporal threshold $\theta_t$ are pre-determined. Then, the most qualified POI trajectory $Tra$ should have a high total experience value $\sum_{POI_k\in Tra} as_k$, and its total spatial and temporal distances should not exceed thresholds. Finally, $Tra$ will be recommended for a user group.

$$\begin{aligned} &Dist(POI_i, POI_j) \\ &\quad = R\cdot arccos[cos(POI_i.x)\cdot cos(POI_j.x) \\ &\qquad \cdot cos(POI_j.y - POI_i.y) + sin(POI_i.x)\cdot\ sin(POI_j.x)] \end{aligned} \tag{15}$$

$$Int(POI_i, POI_j) = |POI_j.t - POI_i.t| \tag{16}$$

### C. LOCATION-RECOMMENDATION-AWARE VIRTUAL NETWORK EMBEDDING

Based on the aforementioned recommendation result of POI trajectories, we design a novel location-recommendation-aware virtual network embedding heuristic for optical-wireless hybrid networks supporting 5G models. In this heuristic, we embed the virtual networks with similar recommended POI trajectories into the same DC of the substrate infrastructure. The main step of the heuristic with the pseudo code in **Algorithm 1** is described as follows.

*Step 1:* We divide $N_{ug}$ virtual networks into $M$ sets, and the virtual networks in every set have similar recommended POI trajectories.

*Step 2:* In a certain set of virtual networks, one virtual network will first be mapped into the substrate DC that has a high node degree and available computing resources. After determining the substrate DC $dc^*$, we compute candidate paths from every substrate end device to $dc^*$. The bandwidth provisioning of links along these $N_{ed}^{vn}$ substrate paths are updated, and the computing-resource capacity of $dc^*$ is updated as well.

*Step 3:* The profitability of advertisement targeting will be computed until an attempt has been made to embed all virtual networks into the substrate infrastructure. Moreover, the value of $T$ should not exceed $N_{ug}/M$.

*Step 4:* The energy consumption for inter-DC path establishments is also computed until an attempt has been made to embed all virtual networks into the substrate infrastructure. Note that only when there is more than one DC accepting virtual networks with similar POI trajectories will the energy consumption of inter-DC path establishments be computed.

### D. TIME COMPLEXITY ANALYSIS

As in **Algorithm 1**, we will execute step 1 and step 2 $M$ times, and then the corresponding time complexity is $O[M\cdot(N_{ug} + |sub\_w|\cdot|v_s|)]$. With the inclusion of step 3 and step 4, the final time complexity is about $O[M\cdot(N_{ug} + |sub\_w|\cdot|v_s| + 2\cdot|D_s| + |dc\_w|)]$.

## V. SIMULATION RESULTS AND DISCUSSIONS

We first discuss the rational setting of parameters utilized in our location recommendation methodologies based on the

**Algorithm 1** Pseudo Code of Location-Recommendations-Aware Virtual Network Embedding

**Input:** $G_s(V_s, D_s, E_s)$, $C_{DC}$, $N_{ug}$, $c$, $ba$, $M$, $T$, $Pay$
**Output:** Profitability of advertisement targeting, $Pro$; Total energy consumed by establishing inter-DC paths, $E$

1: Initialization: $Pro \leftarrow 0$, $E \leftarrow 0$, the set of $N_{ug}$ virtual networks: $w \leftarrow \{G^1_{vn}, G^2_{vn}, ..., G^{N_{ug}}_{vn}\}$, and $N^{vn}_{ed} = ranf(2, \lceil |E_s|/(|V_s| + |D_s|) \rceil)$;
2: **for** $i = 1, 2, ..., M$ **do**
3: Initialize the set of virtual networks with similar POI trajectories: $sub\_w \leftarrow Null$;
4: **for** $\{G^1_{vn}, G^2_{vn}, ..., G^{N_{ug}}_{vn}\} \in w$ **do**
5: $sub\_w \leftarrow sub\_w + \{G^k_{vn} | G^k_{vn}.group\_index = i\}$;
6: **end for** /* Line 4 → Line 6: step 1; time complexity: $O(N_{ug})$ */
7: **for** $G^k_{vn} \in sub\_w$ **do**
8: Determine the substrate DC: $dc^* \leftarrow \{dc | C_{DC} \geq c, arg_{max}[node\_degree(dc)]\}$;
9: **for** $j = 1, 2, ..., |V_s|$ **do**
10: Update the set of candidate paths: $P \leftarrow P + \{pa_k \leftarrow Dijkstra(j, dc^*)\}$;
11: **end for**
12: **if** $|P| \geq N^{vn}_{ed}$ **then**
13: Select $N^{vn}_{ed}$ shortest ones as substrate paths from $P$;
14: Update the bandwidth provisioning of links along these $N^{vn}_{ed}$ substrate paths;
15: Update the computing-resource capacity of $dc^*$;
16: **end if**
17: **end for** /* Line 7 → Line 17: step 2; time complexity: $O(|sub\_w| \cdot |V_s|)$ */
18: **end for**
19: **for** $|D_s|$ DCs **do**
20: **for** $i = 1, 2, ..., M$ **do**
21: Count the number $T_i$ of successfully embedded virtual networks with the group index $i$;
22: **if** $T_i > T$ **then**
23: $Pro \leftarrow Pro + T_i \cdot Pay$;
24: **end if**
25: **end for**
26: **end for** /* Line 19 → Line 26: step 3; time complexity: $O(|D_s| \cdot M)$ */
27: **Return** $Pro$;
28: **for** $i = 1, 2, ..., M$ **do**
29: Initialize the DC set: $dc\_w \leftarrow Null$;
30: **for** $DC_1, ..., DC_j, ..., DC_{|D_s|}$ **do**
31: Count the number $T^j_i$ of successfully embedded virtual networks with the group index $i$ for $DC_j$;
32: **if** $T^j_i > 0$ **then**
33: Update the DC set: $dc\_w \leftarrow dc\_w + DC_j$, ascending $(T^j_i)$;
34: **end if**
35: **end for**
36: $DC_{src} = dc\_w.top()$;
37: $dc\_w.pop()$;
38: **for** $DC_k \in dc\_w$ **do**
39: $pa_k \leftarrow Dijkstra(DC_{src}, DC_k)$;
40: $E \leftarrow E + E(pa_k)$;
41: **end for**
42: **end for** /* Line 28 → Line 42: step 4; time complexity: $O[(|D_s| + |dc\_w|) \cdot M]$ */
43: **Return** $E$.

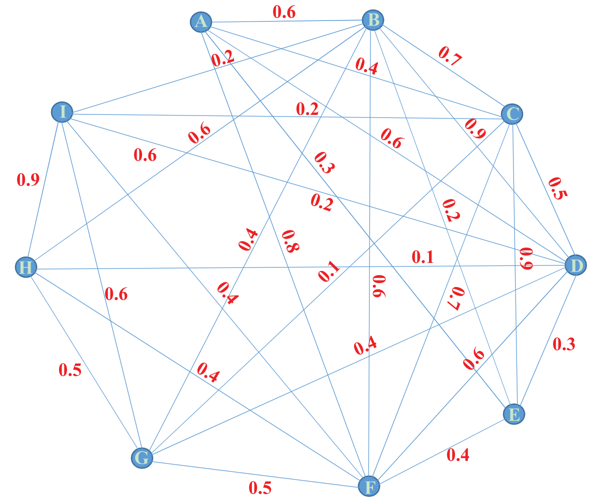


**FIGURE 5.** Real-data-based graph recording direct relationship degree among users in a group.

given auxiliary user-location graph for one user group, where five males and three females are included. The direct relationship degree among users is pre-determined by tracking the actual data from life, and this is shown by the number beside the graph edge in Fig. 5, which only demonstrates the upper part of Fig. 4. The users rank the initial hub score based on the real status data published in the network chat software. Five kinds of POIs with a total of 22 actual candidate locations (4 hotels, 3 stations, 4 educations, 6 shops and 5 canteens) are involved in our simulations so that there will be at most $4 \times 3 \times 4 \times 6 \times 5 = 1440$ recommended POI trajectories.

### A. SIMULATION RESULTS OF LOCATION RECOMMENDATION METHODOLOGIES

As demonstrated in Eq. (10), the initial hub score plays the more important role in updating the authority score if we have a large $\beta$, thus making the authority-score difference among various kinds of locations for a POI small. As in Fig. 6, where four locations of the 'hotel' POI are only considered, the large $\beta$, especially when $\beta = 0.9$, makes the recommendation of a stand-alone POI difficult since the authority-score difference is very narrow. Therefore, the rational value of $\beta$ will be set so that the effect of the initial hub score on the authority score updating weakens, such as the case $\beta = 0.4$ in Fig. 6

As mentioned in section IV, the spatial and temporal thresholds both decide whether we can recommend a POI trajectory for the user group; thus, their rational value range cannot exceed the maximal spatial or temporal length. Then, we obtain the threshold by letting the maximal length be multiplied by an increasing factor smaller than one. In Fig. 7, we can see that the number of POI trajectories grows with the rise in the spatial threshold, but this tendency will finally tend to be stable. Moreover, the rational value of the spatial threshold should be set to obtain the largest number of

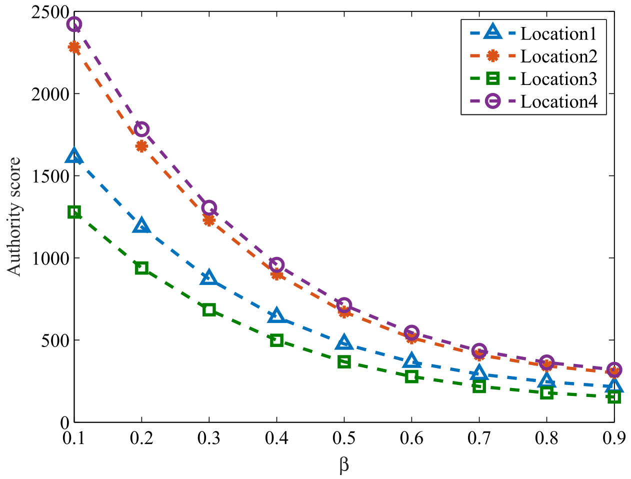


**FIGURE 6.** Authority score of one POI vs. $\beta$.

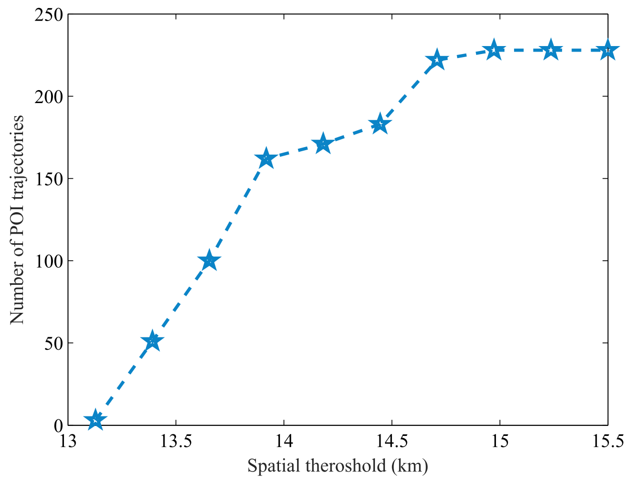


**FIGURE 7.** Number of POI trajectories vs. spatial threshold.

POI trajectories (e.g., the rational spatial threshold should have 15km in Fig. 7). Figure 8 demonstrates the similar variation tendency and the value setting for the temporal threshold.

## B. SIMULATION RESULTS OF PROFITABILITY

The test topology with 24 nodes (i.e., $|V_s| + |D_s| = 24$) and 49 links (i.e., $|E_s| = 49$) is shown in the right part of Fig. 1(b); its average node degree is 3, i.e., the number of users in one group $N_{ed}^{vn} = ranf(2, 3)$. We let $c = ba = Pay = 1$. We obtain four sets (i.e., $M = 4$) of virtual networks followed by our recommendation methodologies, and the virtual networks in every set have similar POI trajectories. The benchmark is the traditional virtual network embedding algorithm without the awareness of location recommendations [8], [9]. In the benchmark, the virtual networks will be embedded into the substrate network as many as possible, while the virtual networks with similar recommended results cannot be screened out and they would be scattered in different DCs, thus leading to the high energy-consumption of inter-DC path establishment and low profitability for

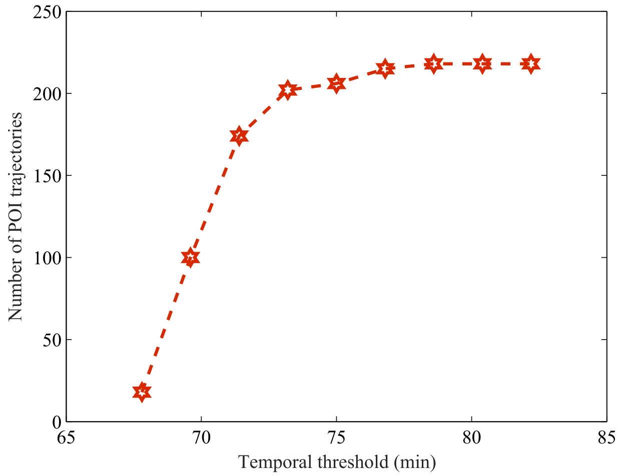


**FIGURE 8.** Number of POI trajectories vs. temporal threshold.

advertisement targeting. First, as in Fig. 1(b), four nodes labelled 17, 18, 14 and 8 are assumed to be small-scale DCs because their node degree is large, and the remaining nodes are end devices, i.e., $|V_s| = 20$ and $|D_s| = 4$.

We then compare the profitability among the upper bound analyzed by us, our solution and the benchmark with the increase in initial computing-resource capacity assigned for each DC. Based on the bound analysis above, because $C_{DC} = \{50, 60, 70, 80, 90, 100\}$, the corresponding maximal number of virtual networks successfully embedded $N_{max} = \{200, 240, 280, 320, 360, 400\}$, and we let $N_{ug} = N_{max}$. As a result, the upper bound of profitability is also 200, 240, 280, 320, 360, and 400, respectively, because $Pay = 1$, which can be seen in Fig. 9(a). We let $T = N_{ug}/(5 \cdot M)$, i.e., $T = \{10, 12, 14, 16, 18, 20\}$, because the value of $T$ should not be larger than $N_{ug}/M$. The simulation results of Fig. 9(a) show that our solution has higher profitability compared to the benchmark, as only when the number of successfully embedded virtual networks with similar recommended POI trajectories exceeds the threshold will there be the corresponding profitability. In our solution, virtual networks with similar recommended POI trajectories tend to be processed as a single set in the same DC, thus leading to high profitability, and the improvement ratio can be as high as 20% over the benchmark. Moreover, the profitability of our solution is very close to the upper bound, with an average converge ratio of 97%, which demonstrates the optimality of our solution.

Given $C_{DC} = 50$ and $N_{ug} = N_{max} = 200$, we compare the profitability between our solution and benchmark under different settings of the threshold $T = \{5, 10, 15, 20, 25\}$ in Fig. 9(b). We can see that with the increase in $T$, although the profitability of our solution slightly decreases, the improvement ratio of profitability over the benchmark becomes high; the larger the threshold is, the greater is the constraint on the ability of the benchmark to obtain profitability.

Given $C_{DC} = 50$ and $T = 10$, we compare the profitability of our solution and the benchmark with $N_{ug} = \{120, 140, 160, 180, 200\}$ in Fig. 9(c). Although the profitability of the benchmark and our solution becomes high

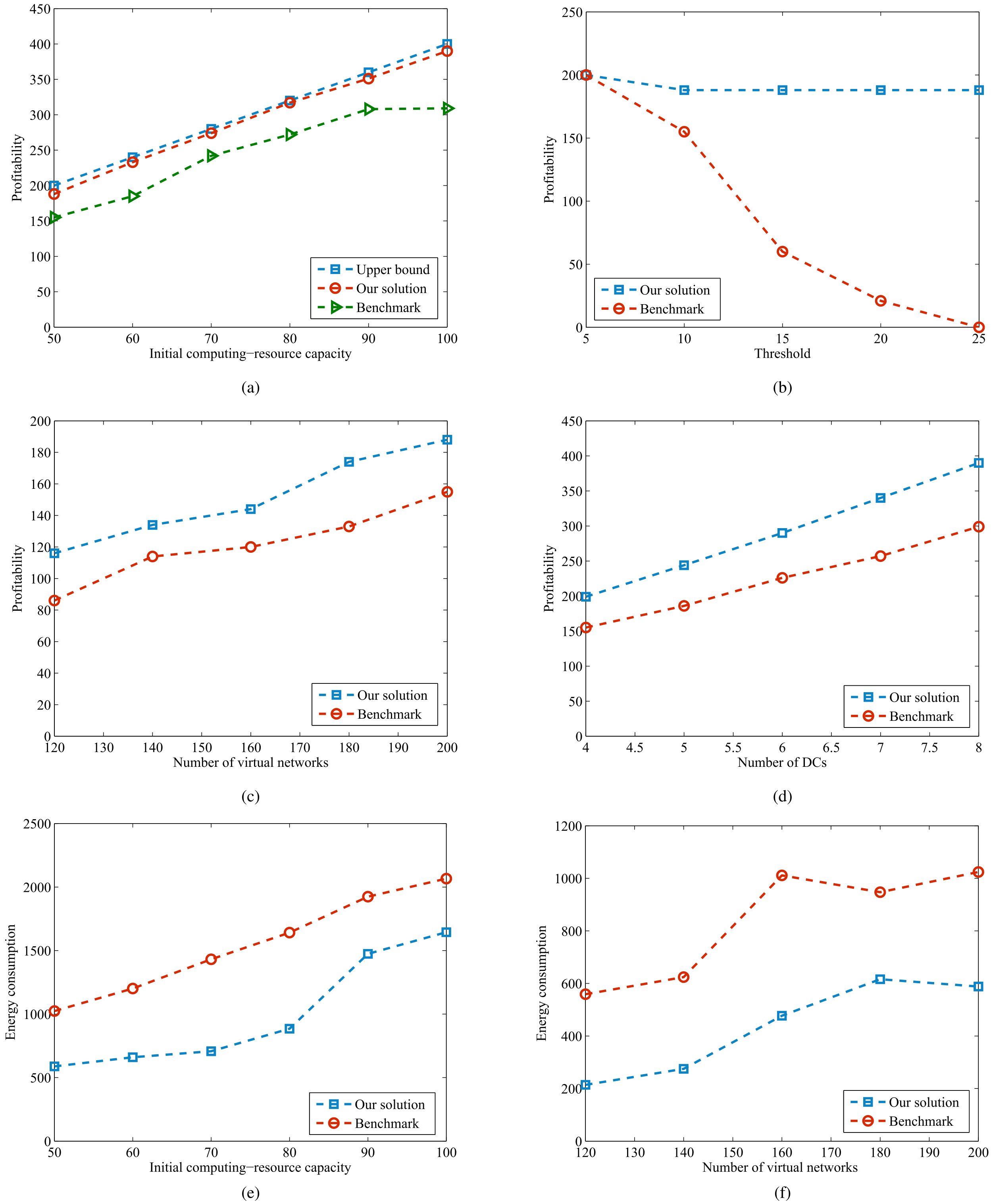


**FIGURE 9.** **Simulation results of profitability and energy consumption. (a) Profitability vs. initial computing-resource capacity. (b) Profitability vs. threshold. (c) Profitability vs. number of virtual networks. (d) Profitability vs. number of DCs. (e) Energy consumption vs. initial computing-resource capacity. (f) Energy consumption vs. number of virtual networks.**

with the increasing number of successfully embedded virtual networks, our solution always has higher profitability than the benchmark.

Finally, given $C_{DC} = 50$ and $T = 10$, we compare the profitability between our solution and the benchmark if the number of DCs in the test topology becomes a variable, i.e., $|D_s| = \{4, 5, 6, 7, 8\}$, in Fig. 9(d). When $|D_s| = 8$, based on the bound analysis, the corresponding maximal number of virtual networks successfully embedded $N_{max} = 400$. Thus, we let $N_{ug} = N_{max} = 400$. We can see that with the increase in $|D_s|$, the profitability of the benchmark and our solution becomes high, and as expected, our solution always has higher profitability than that of the benchmark.

### C. SIMULATION RESULTS OF ENERGY CONSUMPTION FOR INTER-DC PATH ESTABLISHMENTS

Similarly, as in Fig. 1(b), four nodes labelled 17, 18, 14 and 8 are assumed to be small-scale DCs because their node degree is large, and the remaining nodes are end devices, i.e., $|V_s| = 20$ and $|D_s| = 4$. In addition, to facilitate a visualized result demonstration, we make the corresponding normalization processing for energy-consuming parameters $\gamma^s/a_l \approx 1.75, a_l = 1$, which is not measured in Watts because they are natural constants that have negligible influence on the variation tendency of the energy consumption for inter-DC path establishments. According to Eq. (1), this part of energy consumption is related with the number of established inter-DC paths and the number of routing hops owned by those paths.

We first compare the energy consumption for inter-DC path establishments of our solution and the benchmark with the increase in initial computing-resource capacity assigned for each DC, i.e., $C_{DC} = \{50, 60, 70, 80, 90, 100\}$, and we let $N_{ug} = N_{max} = \{200, 240, 280, 320, 360, 400\}$, $T = \{10, 12, 14, 16, 18, 20\}$. The simulation results of Fig. 9(e) demonstrate that our solution has lower energy consumption compared to that of the benchmark because the virtual networks with similar recommended POI trajectories tend to be processed as a single set in the same DC; as a result, the adviser can locally push the corresponding products to users instead of consuming a large amount of energy to establish inter-DC paths. Compared to the benchmark, the improvement ratio of energy efficiency can be as high as 38%.

Next, given $C_{DC} = 50$ and $T = 10$, we compare the energy consumption for inter-DC path establishments of our solution and the benchmark with $N_{ug} = \{120, 140, 160, 180, 200\}$ in Fig. 9(f). Although the energy consumption of the benchmark and our solution becomes fairly high with the increasing number of successfully embedded virtual networks, our solution always has lower energy consumption compared to the benchmark.

## VI. RELATED WORK

Because location recommendation is a broad topic, in this section, we focus on 5G-based location recommendation, which can be divided into two categories based on the objective of their recommendation: 1) stand-alone POI recommendation systems that provide users with individual locations that match its preferences [4]–[6], and 2) sequential location recommendation systems that recommend a series of locations to a user based on its preferences and some constraints in terms of temporal and spatial distances. Compared to the stand-alone POI recommendation, user-generated trajectories contain a richer set of information, such as the path travelled. As a result, the trajectory data can be used to more accurately estimate a user's preferences [7]. However, the aforementioned works only focused on the location recommendation for a user, not a user group. More importantly, the specific application of the recommendation results has not been adequately discussed, for example, advertisement targeting based on location recommendations, as mentioned in our work.

In the case of virtual network embedding, existing works mainly proposed corresponding design frameworks tailored to traditional optical data center networks [11]–[13]. In particular, the authors in [11] and [12] presented a model that reflects the linear power growth of fibre links and servers. Based on the variable power consumption information, each user or cloud provider selfishly selected the most power-efficient virtual lightpath. Eventually, the proposed approach exhibited convergence to the global optimum performance. Considering the multi-priority service requests, the authors in [13] proposed a multi-period virtual network embedding. High-priority service requests must be processed instantly, and low-priority service requests can be served anytime within a maximal delay. With the accurate estimation of the time-varying service requests, the least power-consuming virtual lightpaths were found in the current time period. In fact, given the possibility of ubiquitous 5G wireless access, it is necessary to move computing capacity from end devices to DCs for mobile cloud computing services such as advertisement targeting based on location recommendations. Correspondingly, the integration of metro optical and ubiquitous wireless access technologies has become increasingly necessary [8]– [10]. Therefore, the virtual network embedding approaches utilized in traditional optical data center networks cannot be directly utilized for new optical-wireless hybrid networks in accordance with 5G models.

Above all, this paper is the first work to focus on location-recommendation-aware virtual network embedding in energy-efficient optical-wireless hybrid networks supporting 5G models.

## VII. CONCLUSIONS

In this paper, a novel design framework for location-recommendation-aware virtual network embedding has been proposed to minimize the energy consumption associated with inter-DC path establishments in optical-wireless hybrid networks that support 5G models. This problem has been formulated as a scenario in which the profitability of advertisement targeting is maximized. The NP-hardness and upper bound of the transformed problem have been analyzed. To find a solution to the problem that involves a short computation time, a novel heuristic has also been designed. The simulation results have demonstrated that our design framework can obtain higher profitability and energy efficiency with improvement ratios of 20% and 38%, respectively, compared to the benchmark. More importantly, the profitability obtained by our heuristic is very close to the upper bound, with a converging ratio of 97%. Since this paper is the first work to focus on location-recommendation-aware virtual network embedding in optical-wireless hybrid networks supporting 5G models, only the simulation results have been shown. In the near future, a real experiment would be performed in a small-scale testbed with the necessary hardware.

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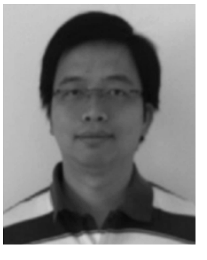

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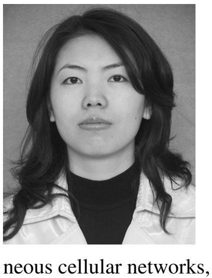

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