Optimal Allocation of Mobile Learning Resources Based on a Complex Network

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Abstract—Currently, centralized online learning can no longer meet the fragmented learning needs of learners. It is a hot topic in mobile learning to allocate reasonable mobile learning resources (MLRs) for user terminals and servers. However, the existing studies have rarely discussed the matching relationship between the MLR features of user terminals and servers. To fill up the gap, this paper tries to optimize the allocation of MLRs based on the theory of mobile knowledge complex network. Firstly, a local bidirectional fitness model was established to optimize MLR allocation, and the core nodes were mined from the complex network of MLRs. Next, the authors clarified the causality between the density of MLR complex network and resource integration, constructed an evaluation index system (EIS) for MLR integration ability, and evaluated the overall resource integration ability of MLR network resources. The proposed network was proved effective in optimizing the resource allocation of mobile learning networks through experiments.

Keywords—complex network, mobile learning resources (MLRs), resource integration, resource allocation

1 Introduction

Under the deep integration between information technology and education, centralized online learning can no longer meet the fragmented learning needs of learners [1-6]. Take English learning for example. The learners can make full use of the scattered time to practice listening training, vocabulary recitation, and short passage reading, while achieving a very high learning efficiency [7-10]. Therefore, mobile learning methods based on mobile terminal devices are increasingly favored by learners. After the generation of mobile learning resources (MLRs), resource providers for the supervision of mobile learning platforms need to ensure the efficiency of resource selection and allocation through a proper execution process [11-18]. In this process, how to allocate reasonable MLRs for user terminals and servers has become a hot issue among mobile learning researchers.

To enable learners to access educational and teaching resources and the learning environment anytime and anywhere, Qun [19] studied domestic and foreign educational and teaching resource databases, designed and implemented an Android-based mobile educational resource management platform, and introduced the overall design of the entire database and the realization method of the front-end display platform, from the perspective of system construction. Zhang et al. [20] proposed an online learning method to meet the service quality requirements of each user, and offered a learning optimization method combined with offline training. Their method can quickly adapt to sudden changes in the average packet arrival rate. Lin et al. [21] advocated feedback-based online resource allocation, and designed an online queue resource allocation algorithm based on Lyapunov optimization. The algorithm was utilized to optimize the resource allocation strategy immediately after the arrival of users. Liu et al. [22] investigated the personalized recommendation algorithm of learning resources, and developed a personalized learning model based on the recommendation algorithm. Their algorithm can analyze the historical learning data of users in mobile learning terminals, and recommend learning resources accurately according to the learning level and personal preference of users. To increase e the utilization of mobile terminals in primary education, Areias et al. [23] explored how mobile phones as a teaching resource can become a part of daily school life in its diverse learning spaces, providing a practical measure to make teaching contents more meaningful and motivating.

The existing studies on the optimal allocation of MLRs ignore the situational factors of the mobile learning environment, and rarely discussed the matching relationship between the MLR features of user terminals and servers. To fill up the gap, this paper tries to optimize the allocation of MLRs based on the theory of mobile knowledge complex network. The main contents are as follows: (1) setting up a local bidirectional fitness model to optimize MLR allocation; (2) describing the importance of any node in a community by relative centrality, and mining the core nodes in the complex network of MLRs; (3) clarifying the causality between the density of MLR complex network and resource integration; (4) constructing an evaluation index system (EIS) for MLR integration ability, and evaluating the overall resource integration ability of MLR network resources. The proposed network was proved effective in optimizing the resource allocation of mobile learning networks through experiments.

2 Network construction

This paper defines the MLR complex network as follows: The user terminals or servers waiting for MLR allocation are abstracted as nodes, while the relationships between user terminals and servers (e.g., information exchange and resource sharing) are abstracted as the edges between nodes. In addition, each community in the MLR complex network is viewed as a local network. Figure 1 explains the idea of MLR allocation. Since the demand of user terminals or servers for learning resources changes in real time, the relationships between different user terminals or servers also vary constantly. For various reasons, old user terminals or servers will choose to leave the community, and new user terminals or servers will choose to join the community. Referring to the fitness model and the local evolution network model, this paper comprehensively considers the features of the community structure and information asymmetry of the MLR complex network, and constructs a local bidirectional fitness model to optimize MLR allocation.

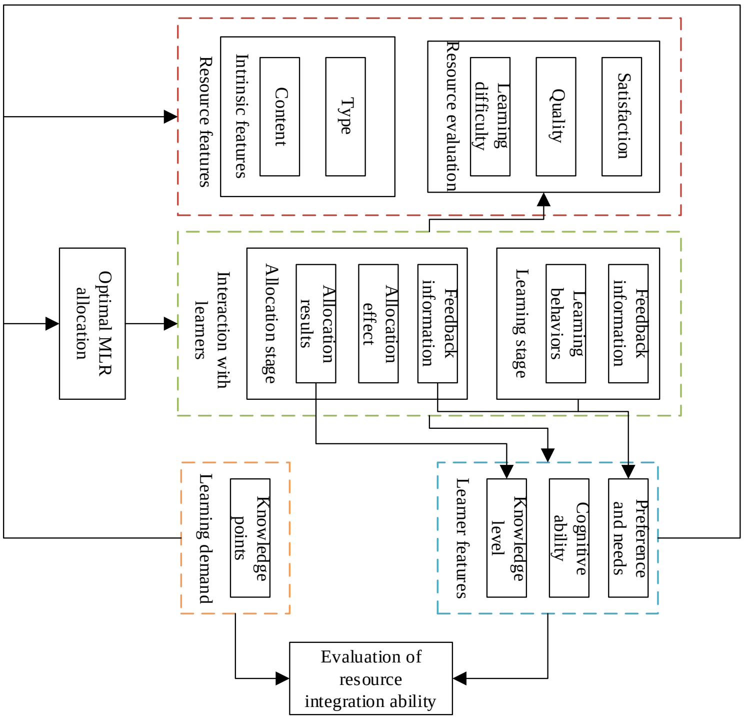

Fig. 1. Idea of MLR allocation

Suppose the MLR complex network initially has n communities of user terminals or servers. Each community contains n_0 user terminals or servers, and d_0 edges between the user terminals or servers. In each unit time period, five operations will occur:

Operation 1: Add a community containing n_0 nodes and d_0 edges at the probability of t.

Operation 2: Add a node u into any known community Φ at the probability of w, and connect the node to the nodes already in the community via n_1 new edges. Let b_i be the out-degree of node i. Then, view nodes u and i as an MLR and a user terminal/server, respectively. Link u with node i in Φ via a directed edge. Then, the probability of choosing node i can be calculated by:

$$\prod(b_i) = \frac{b_i}{\sum_{j\in\Phi} b_j} \tag{1}$$

As user terminals or servers have their own preferences for MLRs, it is assumed that the in-degree of node i is l_i. Then, the probability of choosing node i can be calculated by:

$$\prod(l_i) = \frac{l_i}{\sum_{j\in\Phi} l_j} \tag{2}$$

Combining formulas (1) and (2):

$$\prod(l_i) = \frac{\alpha l_i}{\sum_{j\in\Phi} l_j} \tag{3}$$

If α=1, l_i is the out-degree of node i; if α=-1, l_i is the in-degree of node i. This operation is repeated n_1 times.

Considering the sheer number and diversity of MLRs in the real world, the fitness of each MLR node determines its optimal allocation. The fitness of each MLR node is selected by probability distribution $\sigma(\delta)$. Then, we have:

$$\prod(l_i) = \frac{\alpha \delta_i l_i}{\sum_{j\in\Phi} \delta_j l_j} \tag{4}$$

Operation 3: Add n_2 edges to any known community at the probability of s. First, select one end of any edge in the community, and choose the other end of that edge by formula (4). Repeat this operation n_2 times.

Operation 3. Remove n_3 edges from any known community at the probability of r. Let $M_\Phi(s)$ be the total number of nodes in Φ. First, select one end of any edge in the community, and choose the other end of that edge at the probability below:

$$\prod{}^*(l_i) = \frac{1}{M_\Phi(p)-1}\left(1-\prod(l_i)\right) \tag{5}$$

Repeat this operation n_3 times.

Operation 5: Establish n_4 long edges between any two known communities at the probability of v. First, select a node as one end of the edge in any known community by the probability calculated by formula (3), and choose a node as the other end in another known community by that probability. Repeat this operation n_4 times. The above parameters satisfy $0<w<1$, $0\leq t$, s, r and $v<1$, $t+w+s+r+v=1$, and $0\leq\delta\leq 1$.

Based on continuum theory and mean field theory, the degree distribution of node i of user terminals or servers in the community can be obtained. Assuming that l_i changes continuously, the rate of change of l_i can be derived as follows:

First, create a new community, where the degree distribution of node i does not vary with time, at the probability of t. Since the new community is not correlated with any known community, we have:

$$\frac{\partial l_i}{\partial p} = 0 \tag{6}$$

Add a new node into any known community Φ at the probability of w. Then, the change rate of l_i depends on the random selection and preferential selection of MLRs by the community:

$$\frac{\partial l_i}{\partial p}=\frac{n_1 w}{n+pt}\frac{\alpha\delta_i l_i}{\sum_{j\in\Phi}\delta_j l_j} \tag{7}$$

Add n_2 edges to Φ at the probability of h. Then, we have:

$$\frac{\partial l_i}{\partial p}=\frac{sn_2}{n+pt}\left[\frac{1}{M_\Phi(p)}+\left(1-\frac{1}{M_\Phi(p)}\right)\right]\frac{\alpha\delta_i l_i}{\sum_{j\in\Phi}\delta_j l_j} \tag{8}$$

Remove n_3 edges from any known community at the probability of r. Then, we have:

$$\frac{\partial l_i}{\partial p}=\frac{rn_2}{n+pt}\left[\frac{1}{M_\Phi(p)}+\left(1-\frac{1}{M_\Phi(p)}\right)\frac{1}{M_\Phi(p)-1}\left(1-\frac{\alpha\delta_i l_i}{\sum_{j\in\Phi}\delta_j l_j}\right)\right] \tag{9}$$

Formula (9) shows that the connectivity decreases for two reasons: the random selection of one end of the removed edge, and the anti-preferential selection within the community.

Establish n_4 long edges between any two known communities at the probability of v. Then, we have:

$$\frac{\partial l_i}{\partial p}=vn_4\left[\frac{2}{n+pt}\frac{\alpha\delta_i l_i}{\sum_{j\in\Phi}\delta_j l_j}-\frac{1}{n+pt}\frac{1}{n+pt}\left(1-\frac{\alpha\delta_i l_i}{\sum_{j\in\Phi}\delta_j l_j}\right)\right] \tag{10}$$

So far, the authors have strictly solved the degree distribution of the proposed local bidirectional fitness model. The following section will mine the core nodes of the initial MLR complex network.

3 Core node mining

During the optimization of MLR allocation, the authors attach relatively more importance to the resource-demanding core user terminals or servers in the community network, as well as the relative importance between the core user terminals or servers in different communities. Figure 2 illustrates the community structure of an MLR complex network. This paper describes the importance of any node in the community with relative centrality. Let M be the network size; $l_{a\text{-}in}$ and $l_{a\text{-}out}$ be the in-degree and out-degree of node a, respectively; D_{max} be the maximum node, i.e., the root node s. Then, we have:

$$D_{\max}\left(a\right)=\left(l_{a-in}+l_{a-out}\right)/2\left(M-1\right) \tag{11}$$

For a given MLR complex network $H(U, D)$, it is assumed that the core node s belong to H. Let x_s and x_i denote the core node and node fitness coefficient, respectively ($0 \le x_s \le 1$, i=1, 2, …, m). Then, the importance of a node in the community relative to the core node s can be calculated by:

$$QU\left(p_i / s\right)=\frac{x_i D_{RDi}}{x_s D_{RDmax}} \tag{12}$$

The importance function of node p ca be defined as the mean importance of p relative to each node in the set S of core nodes. Then, we have:

$$QU\left(p / S\right)=\frac{1}{|S|}\sum_{s \in S} QU\left(p / s\right) \tag{13}$$

Formula (13) can be used to evaluate the relative importance of the nodes in different communities:

$$QU_i=\frac{x_i D_{RDi}}{QU\left(p / S\right)} \tag{14}$$

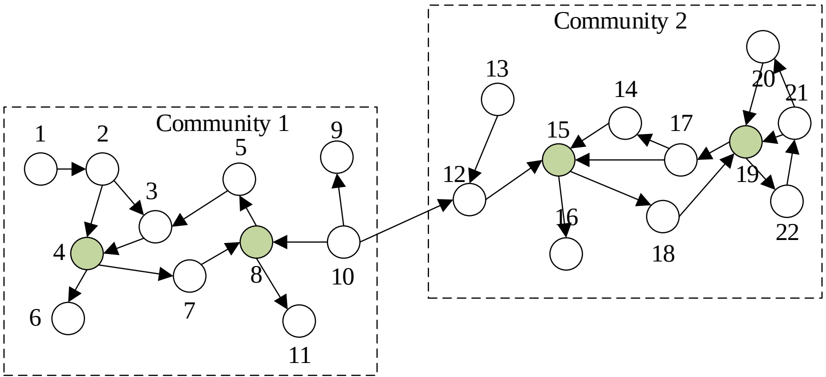

Fig. 2. Community structure of an MLR complex network

4 Evaluation of MLR integration ability

The previous section defines and analyzes the resource allocation of MLR complex network. On this basis, this section tries to evaluate the resource integration ability of this network. Figure 3 presents the causality between network density and resource integration. Drawing on the structural features of the network, the scale of MLRs, and the definition of MLR integration ability, this section sets up an EIS for MLR integration ability of MLR complex network, which can be evaluated comprehensively from four aspects: the breadth, depth, speed, and openness of MLR integration.

The breadth of MLR integration can be measured by MLR volume U_{11}, as well as type of learning resources and demand for different types of resources U_{12}. The depth of MLR integration can be measured by community cohesion U_{21}, high-quality MLR utilization U_{22}, MLR clustering ability U_{23}, and new MLR mining ability U_{24}. The speed of MLR integration can be measured by mining speed of new MLRs U_{31}, transmission speed of network information U_{32}, and MLR clustering speed U_{33}. MLR integration openness can be measured by the inter-community degree of information communication U_{41}, and the degree of information sharing U_{42}. Figure 4 presents the proposed EIS for MLR integration ability.

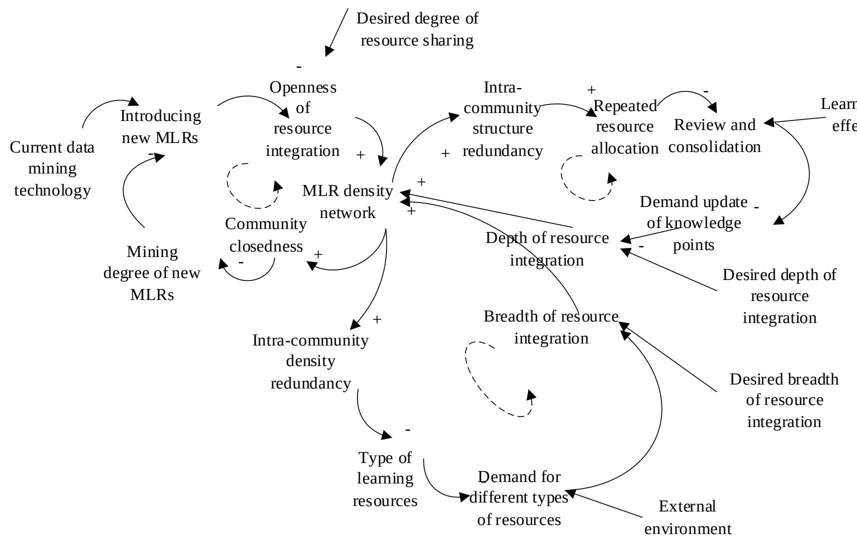

Fig. 3. Causality between network density and resource integration

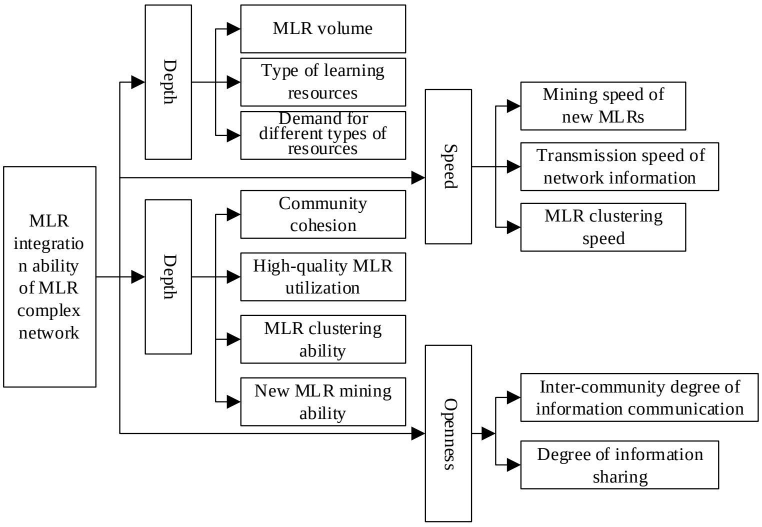

Fig. 4. EIS for MLR integration ability

This paper applies analytical hierarchy process (AHP) to determine the weight vectors $X=(x_1,x_2,x_3,x_4)$ of indices $V_i(i=1,2,3,4)$, where $x_i\geq 0$, and $\Sigma^4_{i=1}x_i=1$. The weight set of the secondary indices U_{ij} can be expressed as $X_i=(x_{i1},x_{i2},...,x_{ij})$, where $x_{ij}\geq 0$, and $\Sigma^{xi}_{j=1}x_{ij}=1$. A total of γ experts were invited to give a score e_{ijl} to each index U_{ij}. In this way, a matrix E of evaluation samples can be obtained as:

$$E=\begin{bmatrix} e_{111} & e_{112} & \cdots & e_{11\gamma} \\ \cdots & \cdots & \cdots & \cdots \\ e_{131} & e_{132} & \cdots & e_{13\gamma} \\ e_{211} & e_{212} & \cdots & e_{21\gamma} \\ \cdots & \cdots & \cdots & \cdots \\ e_{241} & e_{242} & \cdots & e_{24\gamma} \\ \cdots & \cdots & \cdots & \cdots \\ e_{411} & e_{412} & \cdots & e_{41\gamma} \\ e_{421} & e_{422} & \cdots & e_{42\gamma} \end{bmatrix} \tag{15}$$

Let d be the gray class number, where d=1, 2, 3, 4, and 5 stands for strongly high, slightly high, general, slightly low, and strongly low, respectively. If d=1, the grey number μ_1 of the strongly high class belongs to [0,5,10], and the corresponding whitening weight function can be expressed as:

$$g_{1\left(e_{ijl}\right)}=\begin{cases} e_{ijl}/5, e_{ijl}\in[0,5] \\ 1, e_{ijl}\in[5,10] \\ 0, e_{ijl}\notin[0,10] \end{cases} \tag{16}$$

If d=2, the grey number μ_2 of the slightly high class belongs to [0, 4, 8], and the corresponding whitening weight function can be expressed as:

$$g_{2\left(e_{ijl}\right)}=\begin{cases} e_{ijl}/4, e_{ijl}\in[0,4] \\ \left(8\text{-}e_{ijl}\right)/4,\ e_{ijl}\in[4,8] \\ 0, e_{ijl}\notin[0,8] \end{cases} \tag{17}$$

If d=3, the grey number μ_3 of the general class belongs to [0, 3, 6], and the corresponding whitening weight function can be expressed as:

$$g_{3\left(e_{ijl}\right)}=\begin{cases} e_{ijl}/3, e_{ijl}\in[0,3] \\ \left(6\text{-}e_{ijl}\right)/3,\ e_{ijl}\in[3,6] \\ 0, e_{ijl}\notin[0,6] \end{cases} \tag{18}$$

If d=4, the grey number μ_4 of the slightly low class belongs to [0,2, 4], and the corresponding whitening weight function can be expressed as:

$$g_{4\left(e_{ijl}\right)}=\begin{cases} e_{ijl}/2, e_{ijl}\in[0,2] \\ \left(4\text{-}e_{ijl}\right)/2,\ e_{ijl}\in[2,4] \\ 0, e_{ijl}\notin[0,4] \end{cases} \tag{19}$$

If d=5, the grey number μ_5 of the strongly low class belongs to [0,1, 2], and the corresponding whitening weight function can be expressed as:

$$g_{5\left(e_{ijl}\right)}=\begin{cases} 1, e_{ijl}\in[0,1] \\ \left(2\text{-}e_{ijl}\right)/1,\ e_{ijl}\in[1,2] \\ 0, e_{ijl}\notin[0,2] \end{cases} \tag{20}$$

Let a_{ijd} be the grey evaluation coefficient for index U_{ij} to belong to grey class d; a_{ij} be the total grey number for index U_{ij} to belong to each grey class, where $a_{ij}=\Sigma^5{}_{d}=1a_{ijd}$.

The grey evaluation for the d-th grey class given by t experts for index U_{ij} is denoted as $\beta_{ijd}=a_{ijd}/a_{ij}$, and the grey weight vector of index U_{ij} relative to each grey class as $\beta_{ij}=(\beta_{ij1},\beta_{ij2},\beta_{ij3},\beta_{ij4},\beta_{ij5})$. Then, the grey evaluation matrix B_1 for the index U_{ij} under V_i relative to each grey class can be established as:

$$B_1 = \begin{bmatrix} \beta_{i1} \\ \beta_{i2} \\ \cdots \\ \beta_{ij} \end{bmatrix} = \begin{bmatrix} \beta_{i11} & \beta_{i12} & \beta_{i13} & \beta_{i14} & \beta_{i15} \\ \beta_{i21} & \beta_{i22} & \beta_{i23} & \beta_{i24} & \beta_{i25} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \beta_{ij1} & \beta_{ij2} & \beta_{ij3} & \beta_{ij4} & \beta_{ij5} \end{bmatrix} \tag{21}$$

The overall evaluation result of V_i can be described as $Y_i=X_i \cdot B_i=(y_{i1},y_{i2},y_{i3},y_{i4},y_{i5})$. On this basis, it is possible to obtain the total grey weight matrix $B=(Y_1,Y_2,Y_3,Y_4)^T$ for the MLR network resource integration ability. Next, the ability to integrate the MRLs in the network can be evaluated comprehensively, producing the result $Y=X \cdot B=(y_1,y_2,y_3,y_4,y_5)$.

5 Experiments and results analysis

Table 1 lists the mean values of the clustering coefficients, node degrees, in-degrees of nodes, out-degrees of nodes, as well as the number of target nodes and root nodes in the communities of our MLR complex network. The mobile learning platform publishes the MLRs to several user terminals or servers. Table 2 provides the attributes of different mobile terminals. The demand, request frequency, response time, response speed, satisfaction, complaint rate, and accuracy were obtained from the historical allocation data.

Table 1. Eigenvalues of complex network communities

Community number	**1**	**2**	**3**	**4**	**5**
Mean clustering coefficient	0.0028	0.0032	0.0022	0.0034	0.0031
Mean node degree	3.5	3.1511	2.8472	3.4158	3.4
Mean out-degree of nodes	1.5	1.5266	1.3528	1.7253	1.75
Mean in-degree of nodes	1.5	1.5266	1.3528	1.7253	1.75
Number of root nodes	1	2	1	1	1
Number of target nodes	1	3	1	1	2
Community number	6	7	8	9	10
Mean clustering coefficient	0.0036	0.0028	0.0035	0.0031	0.0034
Mean node degree	3.5124	3.5628	3.6	3.6284	3.3262
Mean out-degree of nodes	1.7481	1.7625	1.76	1.7425	1.7289
Mean in-degree of nodes	1.7481	1.7625	1.76	1.7425	1.7289
Number of root nodes	2	1	2	1	1
Number of target nodes	3	3	1	1	1

Table 2. Attributes of different mobile terminals

Node number	MD_1	MD_2	MD_3	MD_4	MD_5	MD_6	MD_7	MD_8	MD_9	MD_{10}
Demand	1.4	1.3	0.7	0.3	0.5	1.4	0.7	0.5	0.1	0.3
Request frequency	7	5	2	7	5	2	5	3	1	4
Response time	42	44	40	46	42	40	43	41	46	40
Response speed	0.85	0.91	0.88	0.92	0.88	0.82	0.93	0.84	0.82	0.95
Satisfaction	95.26	88.47	93.61	88.14	82.47	95.24	86.46	93.28	88.14	87.37
Complaint rate	2.15	2.48	3.48	2.58	2.12	2.84	2.37	2.25	2.85	2.68
Accuracy	0.928	0.914	0.935	0.905	0.935	0.962	0.948	0.927	0.915	0.972

The performance of the proposed complex network was compared with that of the graph mining-based complex network. Figures 5 and 6 compare the mean node degrees and mean clustering coefficients of the two complex networks, respectively. It can be seen that our complex network has a greater connectivity, and a higher degree of node clustering than the reference model. In addition, the complexity of the internal structure of our network was better depicted than that of the reference model. Hence, it is easier to find the MLR demanding nodes in our network than in the reference model. This verifies the feasibility and effectively of our construction method for MLR complex network.

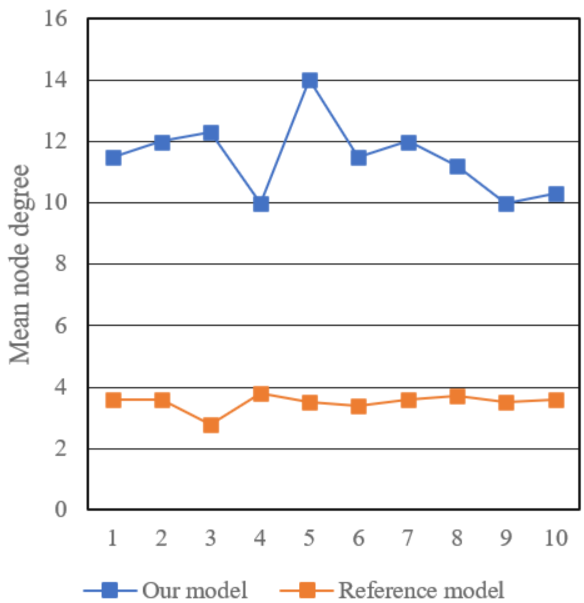

Fig. 5. Mean node degrees of different complex networks

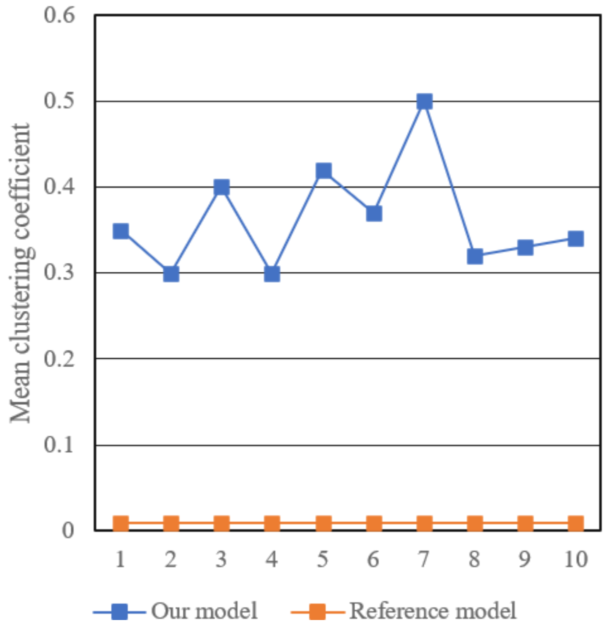

Fig. 6. Mean clustering coefficients of different complex networks

This paper makes a comprehensive evaluation of MLR integration ability from four aspects: breadth, depth, speed, and openness. Figure 7 presents the influence of different factors on resource integration ability. It can be seen that the increase of these factors, e.g., the MLR volume, benefits the ability of the platform to integrate of MLRs. With the growth of each factor, the breadth, depth, speed, and openness of MLR integration increased slowly at the beginning, and rose rapidly after the factors varied by a certain degree.

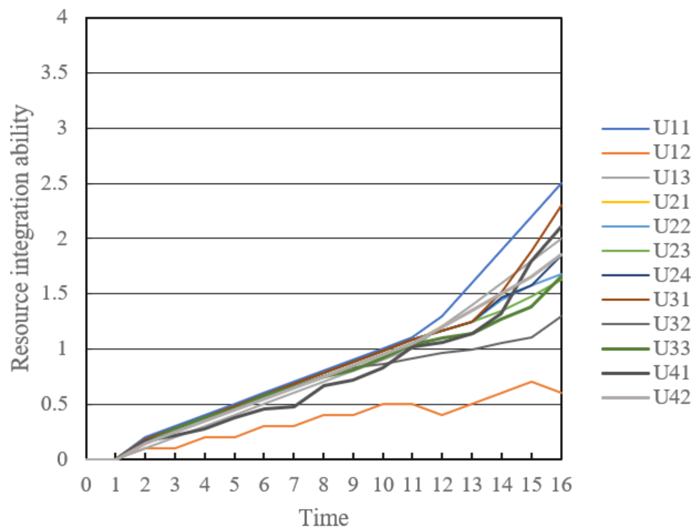

Fig. 7. Influence of different factors on resource integration ability

6 Conclusions

This paper explores the optimization of MLR allocation based on the theory of mobile knowledge complex network. Specifically, a local bidirectional fitness model was built up to optimize MLR allocation, and the core nodes were mined from the MLR complex network. Then, the causality between the density of MLR complex network and resource integration was clarified, followed by the establishment of an EIS for MLR integration ability. On this basis, the resource integration ability of MLR network resources was evaluated comprehensively. Through experiments, the authors summarized the eigenvalues of different complex network communities, and the attributes of mobile terminals. Next, the performance of the proposed complex network was compared with that of the graph mining-based complex network. The comparison shows that our complex network has a greater connectivity, and a higher degree of node clustering than the reference model. Moreover, the complexity of the internal structure of our network was better depicted than that of the reference model. Thus, it is easier to find the MLR demanding nodes in our network than in the reference model. Finally, the authors tested the influence of different factors on resource integration ability, and verified that the breadth, depth, speed, and openness of MLR integration increased rapidly after the factors varied by a certain degree.

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