Network Optimization of Online Learning Resources from the Perspective of Knowledge Flow

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Abstract—To effectively share and recommend knowledge, the online learning platform needs to deliver the most suitable and valuable learning resources to the demanders through the best path at a low cost. The existing studies mostly focus on the evaluation of knowledge flow ability and the extraction of knowledge classification features, but rarely tackle the knowledge flow evolution and network optimization in the light of the management of online learning resources (OLRs). To solve the problem, this paper explores the network optimization of OLRs from the perspective of knowledge flow. Firstly, the evolutionary game of the implicit knowledge flow in the OLR network was analyzed. In addition, an optimization model of OLRs was constructed, according to the evolutionary game mechanism for the implicit knowledge flow in the OLR network based on knowledge sharing, and the self-organizing hierarchical reconstruction. Finally, the network optimization effect was rated, and the network optimization was proved effective, with the management of music OLRs as an example.

Keywords—knowledge flow, online learning resources (OLRs), network optimization

1 Introduction

In the age of online learning, the management of online learning resources (OLRs) attracts much attention from many educators at home and abroad [1-10]. Currently, the studies on knowledge flow have been applied to various fields, including collaborative technology innovation, design of knowledge payment platforms, and networking of industrial cluster manufacturing [11-16]. The knowledge flow theory is a key technique for realizing resource sharing and optimizing learning efficiency. It is innovative to introduce this theory to OLR management. Under OLR management, the learners participating in the learning programs of the online learning platform should achieve more significant learning effect by learning the knowledge in the recommended learning resources. To this end, the online learning platform must deliver the most suitable and valuable learning resources to the demanders through the best path at a low cost in the short query period for learning resources, thereby effectively sharing and recommending knowledge [17-21]. Meanwhile, it is important to balance the demand of each node in the OLR network, so as to realize the collaborative progress of online learning groups.

Anjorin et al. [22] described an ongoing project at Technical University of Darmstadt, which aims to realize a collaborative knowledge acquisition platform based on web resources, and analyzed how CROKODIL supports the various stages of the search process according to the social search model, an important issue in today's learning process. Lee et al. [23] proposed and realized a system resource management mechanism in the web-based distributed e-learning platform Asian Mind. To ensure the quality of content access, the contents of continuous media courses were distributed to the course content server closest to the learner, according to the popularity of course content access.

Higher education institutions are encouraged to build a database of shared e-learning resources based on big data and cloud, because it facilitates and saves the cost for e-learning teachers in data crawling, storage, analysis, processing, optimization, and sharing. Jiang and Xie [24] presented a basic conceptual framework for developing a database of shared e-learning resources based on big data and cloud, and identified the potential benefits for the teachers, students, and university-enterprise connections. The future application of the framework will help relevant teachers to improve the efficiency and effectiveness of data collection, textbook preparation and processing, and user (student) satisfaction, and enhance the efficiency and effectiveness of university-enterprise connections.

Knowledge flow is invisible yet plays an important role in the educational process. Stale and Majors [25] introduced the enterprise modeling method to analyze the knowledge flow in continuing education. The method is not only applicable to educational institutions, but also to commercial organizations. With the aid of the digital ecosystem approach, the enterprise modeling method supports knowledge flow analysis in education and business processes. Virtually no scholar has investigated educational systems as inter-agency networks, especially in the education of information system development. To fill the gap, Strazdina et al. [26] treated the educational system as an inter-agency network, and defined the feedbacks in the network, aiming to improve the overall network performance. Another purpose is to find the datasets required for feedback analysis, and the appropriate methods for data analysis.

Many domestic and foreign researchers have explored and practiced ORL recommendation and management, yielding innovative and practical results. However, the existing studies mostly focus on the evaluation of knowledge flow ability and the extraction of knowledge classification features, but rarely tackle the knowledge flow evolution and network optimization in the light of OLR management. Therefore, there is ample space for developing OLR management methods in the context of knowledge flow. Therefore, this paper explores the network optimization of OLRs from the perspective of knowledge flow. Firstly, Section 2 analyzes the evolutionary game of the implicit knowledge flow in the OLR network. Based on knowledge sharing, Section 3 constructs an optimization model of OLRs was constructed, according to the evolutionary game mechanism for the implicit knowledge flow in the OLR network based on knowledge sharing, and the self-organizing hierarchical reconstruction. Section 4 rates the network optimization effect, and proves the effectiveness of the network optimization, with the management of music OLRs as an example.

2 Evolutionary game analysis

Figure 1 shows the proposed knowledge flow structure of the OLR network, which mainly covers two phases: sharing learning resources, and accepting learning resources. Four influencing factors are covered, including contents of learning resources, knowledge flow media, resource sharers, and resource acceptors.

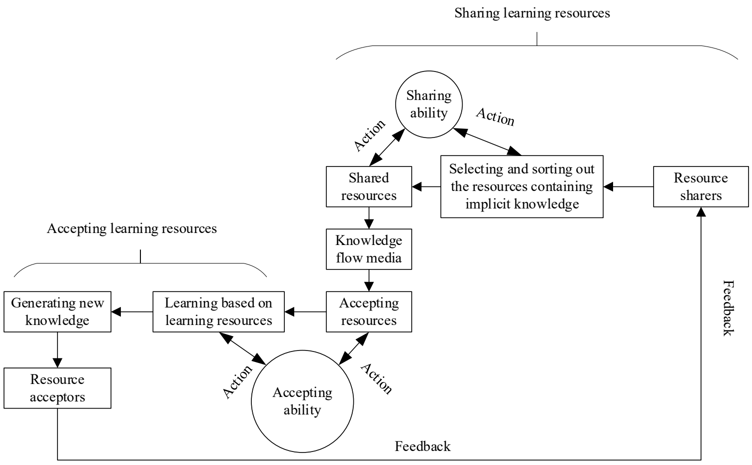

Fig. 1. Knowledge flow structure of the OLR network

Based on knowledge sharing, the OLR network completes knowledge sharing, along with the flow of explicit and implicit knowledge. The explicit knowledge flow has systematic and complete records. In contrast, the implicit knowledge flow depends on experience accumulation, and features poor flowability, complex flow, low sharing degree, and high reward rate for learning. This paper puts forward the following game model to explore the game mechanism for implicit knowledge flow in the OLR network, and to realize collaborative progress of online learners.

Within the knowledge sharing-based OLR network, whether a learner chooses to share knowledge or not depends on the utility of shared learning resources to other learners. Take the game between learners P_1 and P_2 for example. The utility functions v_1 and v_2 of P_1 and P_2 can be respectively expressed as:

$$v_1 = v_1\left\{s_1L_1, \left(y_1 + o\right)x_2L_2, x_2y_1c_1L_1L_2, z_1x_1L_1\right\} \tag{1}$$

$$v_2 = v_2\left\{s_2L_2, \left(y_2 + o\right)x_1L_1, x_1y_2c_2L_2L_1, z_2x_2L_2\right\} \tag{2}$$

where, L_i is the implicit knowledge stock of learner P_i; s_i is the learning reward coefficient of implicit knowledge of learner P_i; x_i is the sharing ability coefficient of implicit knowledge of learner P_i; y_i is the accepting ability coefficient of implicit knowledge of learner P_i; z_i is the flow cost coefficient of implicit knowledge of learner P_i; c_i is the online collaborative progress coefficient of learner P_i; o is the sharing compensation coefficient of implicit knowledge.

In the knowledge sharing-based OLR network, the reward rate for a learner to study learning resources characterized as implicit knowledge is denoted as s_iL_i. After sharing learning resources, the other learners will obtain the added value of the implicit knowledge within the shared resources, and have a learning reward rate of $(y_i+o)x_jL_j$. Through the resource sharing of the OLR network, the implicit knowledge flows between learners, and gets accepted and internalized by many new learners, which give birth to more knowledge value $c_iy_ix_jL_iL_j$. However, knowledge sharing may reduce the competitive advantage of the sharer, generating a negative utility of $d_ix_iL_i$. Figure 2 explains the knowledge appreciation in knowledge flow in OLR network. On this basis, formulas (1) and (2) can be respectively simplified as:

$$v_1 = s_1L_1 + (y_1 + o)x_2L_2 + x_2y_1c_1L_1L_2 - z_1x_1L_1 \tag{3}$$

$$v_2 = s_2L_2 + (y_2 + o)x_1L_1 + x_1y_2c_2L_2L_1 - z_2x_2L_2 \tag{4}$$

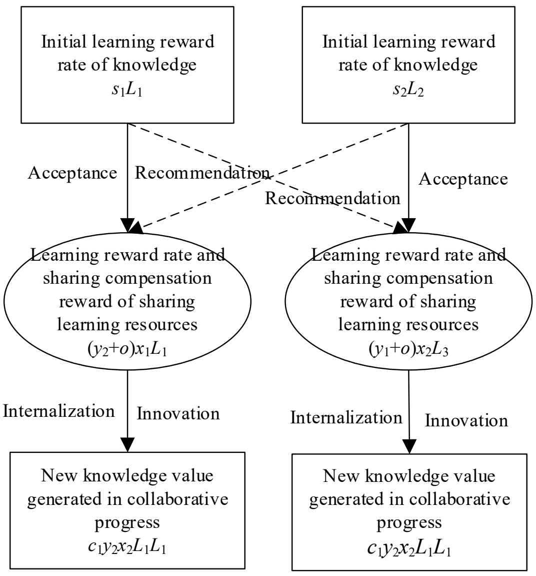

Fig. 2. Knowledge appreciation in knowledge flow in OLR network

Let a denote the probability for learner T_1 choose to share learning resources. Then, the probability for the learner to refuse sharing resources is (1-a). Similarly, let b denote the probability for learner T_2 choose to share learning resources. Then, he probability for the learner to refuse sharing resources is (1-*b*).

According to the game relationship between learners in the knowledge sharing-based OLR network, the expected learning reward rate V_{11}(sharing) / V_{12}(not sharing) and mean learning reward rate V_1^* can be calculated for different choices made by learner P_1:

$$v_1 = b\left[s_1L_1 + \left(y_1 + o\right)x_2L_2 + x_2y_1c_1L_1L_2 - z_1x_1L_1\right] + \left(1-b\right)\left(s_1L_1 - z_1x_1L_1\right) \tag{5}$$

$$V_{12} = bs_1L_1 + \left(1-b\right)s_1L_1 \tag{6}$$

$$V_1^* = aV_{11} + \left(1-a\right)V_{12} = abx_2L_2\left(y_1 + o + y_1c_1L_1\right) - az_1x_1L_1 + s_1L_1 \tag{7}$$

Similarly, the expected learning reward rate V_{21}(sharing)/V_{22}(not sharing) and mean learning reward rate V_2^* can be calculated for different choices made by learner P_2:

$$v_{21} = a\left[s_2L_2 + \left(y_2 + o\right)x_1L_1 + x_1y_2c_2L_2L_1 - z_2x_2L_2\right] + \left(1-a\right)\left(s_2L_2 - z_2x_2L_2\right) \tag{8}$$

$$V_{22} = bs_2L_2 + \left(1-a\right)s_2L_2 \tag{9}$$

$$\overline{V}_2 = bV_{21} + \left(1-b\right)V_{22} = abx_1L_1\left(y_2 + o + y_2c_2L_2\right) - bz_2x_2L_2 + s_2L_2 \tag{10}$$

On this basis, the replicator equations of the game dynamics for the learners in the knowledge sharing-based OLR network can be established as:

$$\begin{cases} G\left(a\right) = \dfrac{da}{dp} = a\left(V_{11} - \overline{V}_1\right) = a\left(1-a\right)\left\{b\left[x_2L_2\left(y_1 + o + y_1c_1L_1\right) - z_1x_1L_1\right]\right\} \\ G\left(b\right) = \dfrac{db}{dp} = b\left(V_{21} - \overline{V}_2\right) = b\left(1-b\right)\left\{a\left[x_1L_1\left(y_2 + o + y_2c_2L_2\right) - z_2x_2L_2\right]\right\} \end{cases} \tag{11}$$

Suppose $G(a)$=0 and $G(b)$=0. Five optimal local equilibrium points can be obtained to reflect the optimal collaborative progress of online learners, namely, X(0,0), Y(0,1), Z(1,1), W(1,0), and $O(a_0,b_0)$, where a_0 and b_0 can be respectively expressed as:

$$a_0 = \frac{z_2x_2L_2}{x_1L_1\left(y_2 + o + y_2c_2L_2\right)} \tag{12}$$

$$b_0 = \frac{z_1x_1L_1}{x_2L_2\left(y_1 + o + y_1c_1L_1\right)} \tag{13}$$

This paper judges which equilibrium points out of X(0,0), Y(0,1), Z(1,1), W(1,0), and $O(a_0,b_0)$ are the optimization strategy for the OLR network, using the Jacobian matrix of the equation set (11). Firstly, the partial derivative of the equation set is solved to obtain the expression of the Jacobian matrix:

$$J = \begin{bmatrix} (1-2a)\left[bx_2L_2\left(y_1+o+y_1c_1L_1\right)-z_1x_1L_1\right] & a(1-a)\left[x_2L_2\left(y_1+o+y_1c_1L_1\right)\right] \\ b(1-b)\left[x_1L_1\left(y_2+o+y_2c_2L_2\right)\right] & (1-2b)\left[ax_1L_1\left(y_2+o+y_2c_2L_2\right)-z_2x_2L_2\right] \end{bmatrix} \quad (14)$$

The trace of the matrix can be expressed as:

$$\begin{aligned} trJ &= (1-2a)\left[bx_2L_2\left(y_1+o+y_1c_1L_1\right)-z_1x_1L_1\right] \\ &+(1-2b)\left[ax_1L_1\left(y_2+o+y_2c_2L_2\right)-z_2x_2L_2\right] \end{aligned} \quad (15)$$

The coordinates of $X(0,0)$, $Y(0,1)$, $Z(1,1)$, $W(1,0)$, and $O(a_0,b_0)$ are the probability for selecting an optimization strategy for the OLR network. Thus, $a_0 \in (0,1)$ and $b_0 \in (0,1)$. In formulas (12) and (13), $x_1L_1(y_2+o+y_2c_2L_2)>z_2x_2L_2$ and $x_2L_2(y_1+o+y_1c_1L_1)>z_1x_1L_1$.

3 Construction of network optimization model

This section constructs an optimization model of OLRs, according to the evolutionary game mechanism for the implicit knowledge flow in the OLR network based on knowledge sharing, and the self-organizing hierarchical reconstruction.

In the knowledge sharing-based OLR network, the learning resource matching of network nodes, and the demand layer selection of implicit knowledge are two important issues. Before exploring the two issues, it is assumed that, among all nodes in the OLR network, including those sharing learning resources, the maximum accepting ability between any two nodes for implicit knowledge is Y. In the OLR network, the core nodes are screened first. A core node is defined as a node whose OLRs are most compatible with those of a resource sharing node. As for any other node, the learning and accepting abilities for implicit knowledge between the node and the resource sharing node should be tested, such as to ensure the learning and accepting abilities are sufficient for connecting the two nodes. Let η_{ij} be the accepting ability for the implicit knowledge in the remaining learning resources. The purpose is to maximize the accepting ability Y of the resource sharing node SN:

$$\begin{cases} Y = max\eta_{ij} \\ s.t. \\ 0.5 \le \eta_{ij} < 1; i \in n_i, j = SN \end{cases} \quad (16)$$

Based on the two nodes corresponding to the maximum accepting ability Y, the node whose OLRs are most compatible with those of the SN can be determined, and taken as a core node n_i of the OLR network.

Among the n remaining network nodes, it is necessary to find the node with the strongest accepting ability and the same demand layer for implicit knowledge relative to n_i. Let δ_{ij} be the correlation between the two nodes. The constraint on implicit knowledge demand needs to satisfy $0.4 \le \delta_{ij} < 1$. Then, each remaining network node is matched with n_i to maximize the accepting ability Y:

$$\begin{cases} Y = max\eta_{ij} \\ s.t. \\ 0.5 \le \eta_{ij} < 1; i \in n_i, j \in n \end{cases} \tag{17}$$

Suppose n_j and n_l are strongly correlated with the core node n_i. That is, the two nodes have similar correlations and accepting ability for the implicit knowledge in learning resources as n_i. Then, the three nodes belong to the same demand layer for implicit knowledge. Hence, the first layer of the OLR network can be expressed as $h_1=\{n_i,n_jn_l\}$.

Among the n remaining network nodes, it is necessary to find the node with the strongest accepting ability and the same demand layer for implicit knowledge relative to n_i and n_l. Meanwhile, the constraint on implicit knowledge demand needs to satisfy $0.4\leq\delta_{ij}<1$. Then, each remaining network node is matched with $\{n_j,n_l\}$ to maximize the accepting ability Y:

$$\begin{cases} Y = max\ n_{ij} \\ s.t. \\ 0.5 \le \eta_{ij} < 1; i \in \left\{n_j, n_l\right\}, j \in n \end{cases} \tag{18}$$

Based on the Y value, the core node with highly compatible learning resources and strong correlations can be determined for each layer. In this way, all nodes in the OLR network can be assigned to proper layers, i.e., the optimal path for local flow of implicit knowledge can be determined within the OLR network.

Based on the evolutionary game mechanism for the implicit knowledge flow, and the self-organizing hierarchical reconstruction, the OLR network is optimized. The optimal structure of the new network is shown in Figure 3. Compared with the original network, the new network reduces the repetitive flows of knowledge, facilitates benign knowledge exchange, and fills the gap of knowledge, making it easier to extract and disseminate new knowledge.

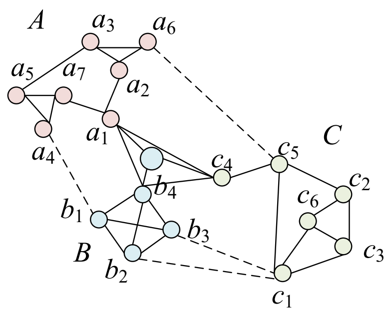

Fig. 3. Optimal structure of the new OLR network

4 Experiments and results analysis

During online learning, the knowledge flow is a progressive activity with ever-changing flow rate. Our experiments target an online learning platform of music. According to the experience in the learning resource recommendations in the previous two years, it was learned that the learners mostly learn the resources on workdays. To better understand the sharing and acceptance of learners for learning resources containing implicit knowledge, the administrator of the online learning platform counts and evaluates the sharing and acceptance states in fixed periods, and adjusts the network optimization strategy for the learning resources accordingly. The intervention of the adjusted strategy promotes the learning effectiveness and the generation of new knowledge. Table 1 presents the scores on network optimization effect, which are based on the optimization results of the subnets of different types of learning resources.

Table 1. Scores on network optimization effect

Class	Videos	Webpage courseware	Images	Videos	Micro-courses	Animations	Virtual simulations	Texts
Correlation score	415	236	352	305	241	269	385	527
Contribution score	468	274	259	317	162	195	281	439
Continuity score	327	195	147	267	124	102	248	395
Mean correlation score	2.17	2.36	2.94	2.48	2.34	2.60	2.81	2.49
Mean contribution score	2.51	2.48	2.69	1.37	1.25	1.33	1.85	2.37
Mean continuity score	1.47	1.16	1.39	1.38	1.20	1.49	1.37	2.07
Number of clicks	195	96	117	135	92	147	162	108
Total score	1347	628	794	928	437	529	817	1472
Mean score	6.19	7.48	6.32	6.83	5.49	5.63	6.18	7.35

Here, the resource acceptance speed is defined as the number of clicks on a learning resource per unit of online learning time, i.e., the number of clicks divided by the click time. Based on the collected data on learning behaviors, the authors analyzed the resource acceptance speed of four types of resources, including texts, audios, videos, and virtual simulations. Figure 4 shows the variation of the resource acceptance speed of each type of resources with learning time.

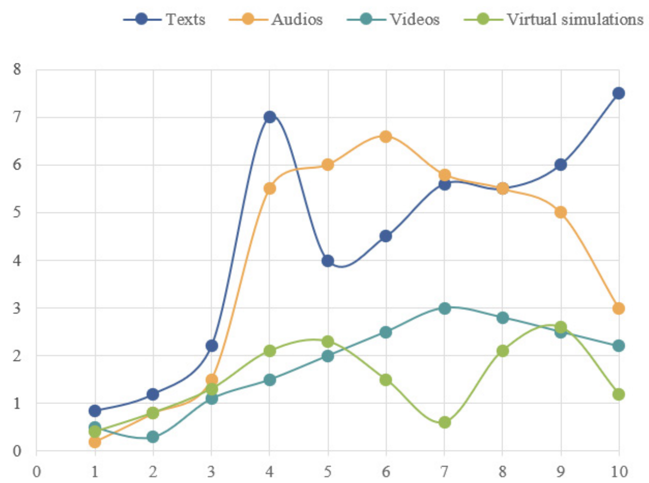

Fig. 4. Time-variation of resource acceptance speed

As shown in Figure 4, the resource acceptance speeds of the four types of resources gradually changed with the online learning time. In the first four learning stages, the learners of texts accepted resources much faster than the learners of the other types of resources. This means the learners being studied prefer text learning resources far more than the other types of resources. Concerning audios and videos, the resource acceptance speeds gradually picked up from the first stage to the peaks in the sixth to seventh stage. For the text learning resources, the initial acceleration changed to a slowdown, yet the resource acceptance speed in the late stages was still faster than the previous stages. For virtual simulations, the speed changed stably with some oscillations, which is associated with the setting of the learning environment.

Figure 5 summarizes the flow difficulties of different types of learning resources. It can be observed that the learning resources of virtual simulations faced the highest difficulty in resource flow, with a score of 93.5. The learning resources of virtual simulations and micro-courses are much harder to flow than those of videos and audios. If a type of learning resources is difficult to flow, it would be hard for learners to share such resources effectively. As a result, the learners would be less enthusiastic about sharing these resources.

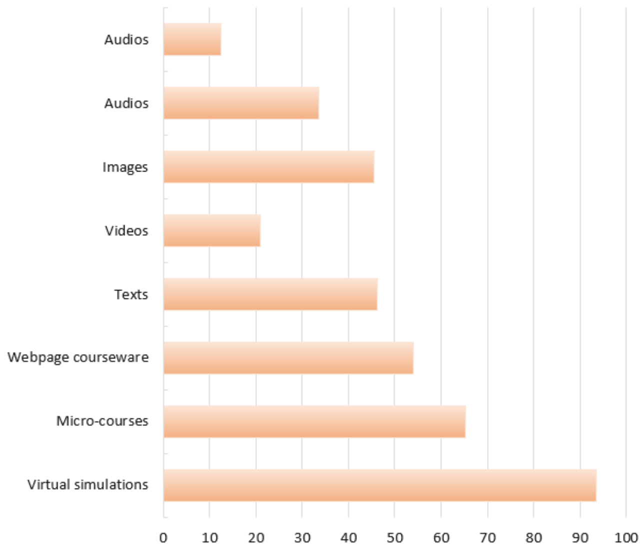

Fig. 5. Flow difficulties of different types of learning resources

Further, resource sharing speed is defined as the swiftness that the state of a learning resource changes from being provided by a node to being accepted by another node: Resource sharing speed = the total number of clicks on the learning resource / ∑(the start time of resource sharing – the acceptance time of the shared resource). Figure 6 shows the variation of the resource sharing speeds of four types of resources with learning time, namely, texts, audios, videos, and virtual simulations. It can be seen that texts and audios were shared much faster than videos and virtual simulations. Thus, the learners being studies prefer to exchange knowledge of learning resources of texts and audios. The sharing speeds of these two types of learning resources almost converged after five to six learning stages.

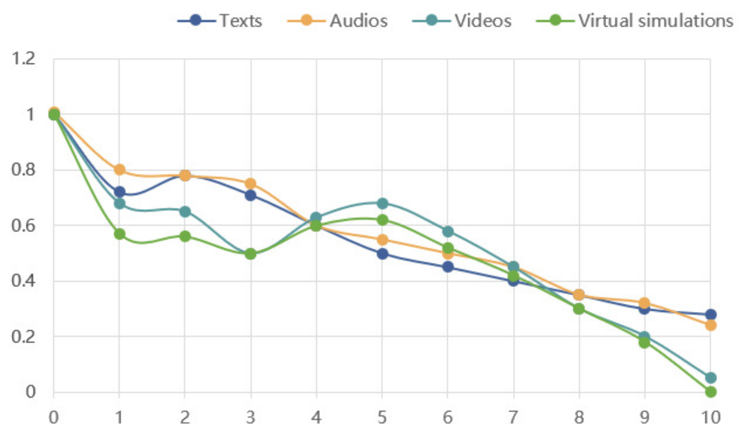

Fig. 6. Time-variation of resource sharing speed

Through the online learning cycle, 4,210 learners were involved in the exchange of four types of learning resources, such as texts, audios, videos, and virtual simulations. The texts were shared by 2,847 learners, the audios by 1,945 learners, the videos by 2,447 learners, and the virtual simulations by 2,140 learners. Figure 7 displays the number of learners of each type of resources in each stage. Obviously, the four types of resources differed significantly in the number of learners. Audios and texts attracted much more learners than the other two types of resources. Hence, the learning resources of texts and audios are more appealing to online learners of music.

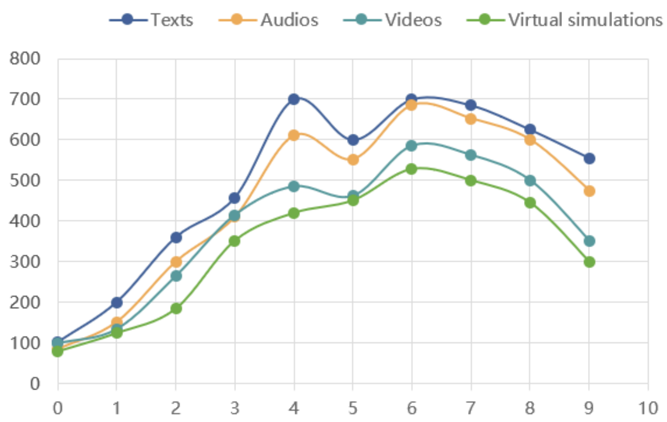

Fig. 7. Flow speeds of four types of learning resources

5 Conclusions

This study attempts to optimize the OLR network from the perspective of knowledge flow. Firstly, the evolutionary game of the implicit knowledge flow in the OLR network was analyzed. After that, the authors built up an optimization model of OLRs, according to the evolutionary game mechanism for the implicit knowledge flow in the OLR network based on knowledge sharing, and the self-organizing hierarchical reconstruction. Taking online music learning for example, the network optimization effect was rated (Table 1) according to the optimization state of the subnet of each type of learning resources. Furthermore, the authors analyzed the time-variation of resource acceptance speed, the time-variation of resource sharing speed, as well as the knowledge flow speeds of four types of learning resources. The flow difficulties of different types of learning resources were also summarized.

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