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Time Optimization of Multiple Knowledge Transfers in the Big Data Environment

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Abstract: In the big data environment, enterprises must constantly assimilate big data knowledge and private knowledge by multiple knowledge transfers to maintain their competitive advantage. The optimal time of knowledge transfer is one of the most important aspects to improve knowledge transfer efficiency. Based on the analysis of the complex characteristics of knowledge transfer in the big data environment, multiple knowledge transfers can be divided into two categories. One is the simultaneous transfer of various types of knowledge, and the other one is multiple knowledge transfers at different time points. Taking into consideration the influential factors, such as the knowledge type, knowledge structure, knowledge absorptive capacity, knowledge update rate, discount rate, market share, profit contributions of each type of knowledge, transfer costs, product life cycle and so on, time optimization models of multiple knowledge transfers in the big data environment are presented by maximizing the total discounted expected profits (DEPs) of an enterprise. Some simulation experiments have been performed to verify the validity of the models, and the models can help enterprises determine the optimal time of multiple knowledge transfer in the big data environment.

Keywords: Big data, knowledge transfer, time optimization, DEP, simulation experiment.

1 Introduction

With the advent of the big data era, big data has become one of the most important factors in production. The rational use of big data indicates the new growth of productivity, which will bring new growth for the production and operations of enterprises [Manyika, Chui, Brown et al. (2012)]. Big data knowledge has become an important part of knowledge that enterprises need for innovation. Many scholars have realized the important role of big data in the development of enterprises and countries. To make full use of the big data knowledge, many researchers consider helping enterprises obtain more big data knowledge from big data using some new optimization algorithms or materials [Fu, Ren, Shu et al. (2016); Liu, Cai, Shen et al. (2016); Kong, Zhang and Ye (2016); Kalidindi, Niezgoda, Landi et al. (2010); Yuan, Li, Wu et al. (2017); Cao, Zhou, Sun et al. (2018)]. The MapReduce proposed

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by Google in 2004 is the most representative data batch processing mode [Dean and Ghemawat (2004); Chen, Alspaugh and Katz (2012)]. Kalidindi [Kalidindi (2010)] built a comprehensive materials knowledge system relying on the use of computationally efficient FFT (Fast Fourier Transforms)-based algorithms for data-mining from large numerical datasets. Some traditional data analysis methods, such as data mining [Wu, Zhu, Wu et al. (2014)], knowledge discovery [Begoli and Horey (2012)], the ontology method [Kuiler (2014)], the statistical analysis method and so on, are applied to acquire knowledge from big data through optimization and adjustment. To ensure the knowledge obtained from big data can be understood and absorbed by enterprises, visualization technology is used to display the final analysis results to the user [Keim, Qu and Ma (2013)].

In the big data environment, the potential intellectual property risk of big data knowledge makes enterprises have to transfer some private knowledge from other organizations while making full use of the big data knowledge [Wu, Chen and Li (2016)]. However, the transfer mode of big data knowledge differs from that of private knowledge. Even though the two types of knowledge are big data knowledge or private knowledge, they are also different from each other in knowledge discovery, the negotiation process and the profit contribution to a new product. Some enterprises need to transfer various types of knowledge in the big data environment. Typically, some types of knowledge are not transferred simultaneously. Enterprises in the big data environment must constantly assimilate private knowledge and big data knowledge through multiple knowledge transfers to maintain their competitive advantage.

Scholars have carried out numerous studies on the influential factors of knowledge transfer and methods to promote the efficiency of knowledge transfer [Khamseh and Jolly (2014); Karlsen and Gottschalk (2015); Szulanski (2000); Burg, Berends and Raaij (2014);Wu and Lee (2015); Hsiao, Chen, Lin et al. (2017); Arteche, Santucci and Welsh (2013); Belso-Martinez (2015); Cowan and Jonard (2004); Fritsch and Kauffeld-Monz (2010); Tang, Mu and Maclachlan (2010); Bagheri, Kusters and Trienekens (2016); Wang and Wang (2017)]. Some scholars believe that the selection of the optimal knowledge time is one of the most important factors to improve the efficiency of knowledge transfer. Farzin [Farzin (1996)] constructed a time optimization model for one type of technical knowledge by maximizing the net present value (NPV). Based on the research of Farzin and others, Doraszelski [Doraszelski (2004)] established an optimal adoption time model for a new technology by using the ordinary differential equation method. By considering the influence of an enterprise's learning effect on the costs, Wu et al. [Wu and Zeng (2009)] proposed a time optimization model of one type of private knowledge in an innovation network. Szulanski [Szulanski (2016)] demonstrated that the proper knowledge transfer time can reduce the transfer difficulties using empirical methods. In previous studies, many scholars noticed the change in knowledge transfer characteristics in the big data environment and the importance of choosing the optimal knowledge transfer time [Wu, Chen and Li (2016); Koman and Kundrikova (2016); Wu (2017)]. However, few researchers have studied the problem of time optimization for multiple knowledge transfers in the big data environment.

This paper categorizes multiple knowledge transfers in the big data environment based on the analysis of the complex process and influential factors. By maximizing the present value of the total expected profit of an enterprise, time optimization models for multiple knowledge transfers are established. These models can help enterprises determine the optimal knowledge transfer time. These models will help enterprises choose the optimal time of knowledge transfer according to different circumstances. After introducing the background of multiple knowledge transfers in the big data environment and the necessity of choosing the optimal time of multiple knowledge transfers in Section 1, the circumstances of multiple knowledge transfers and the modeling method are presented in Section 2. A time optimization model of multiple simultaneous knowledge transfers is presented in Section 3. In Section 4, the simulation experiments and experimental results are described. The conclusions and further research are discussed in Section 5.

2 Modeling method of multiple knowledge transfer in the big data environment

Big data knowledge has the characteristics of being open-source, dynamic, scalable and multi-source heterogeneous [Lohr (2012)]. That makes the process of big data knowledge transfer are significantly different from the process of private knowledge transfer. Big data knowledge transfers have intersectionality and complexity [Wu, Chen and Li (2016)]. An enterprise that transfers one types of big data knowledge has difficulties clearly defining the source of the knowledge transfer. However, the private knowledge transfer is usually a process of knowledge transferring from one organization to another organization [Alavi and Leidner (2001)]. Therefore, the big data knowledge and the private knowledge are the two dominant types of knowledge that enterprises need for innovation.

A new product of an enterprise usually needs various types of knowledge. These types of knowledge may be many types of private knowledge, may be many types of big data knowledge, or may be a variety of mixed knowledge. In addition, these types of knowledge may not be concurrently transferred. Knowledge transfer in the big data environment is a complex process of multiple knowledge transfers among many organizations.

Multiple knowledge transfers in the big data environment can be divided into two circumstances. One is the simultaneous transfer of various types of knowledge, and the other is various types of knowledge transfers at different time points. With the first circumstance, the weights of various types of simultaneous knowledge transfers can be determined by the profit contribution rate of each type of knowledge. Then, the multiple simultaneous knowledge transfers can be seen as a one-time knowledge transfer. By analyzing the influential factors of knowledge transfers, a time optimization model of multiple simultaneous knowledge transfers in the big data environment can be established based on the maximization of the total DEP of a new product. The total DEP includes the DEP before knowledge transfer, the DEP after knowledge transfer and the transfer costs. With the second circumstance, the problem of multiple knowledge transfers in the big data environment can be decomposed into many knowledge transfers. Various types of multiple simultaneous knowledge transfers still can be seen as a one-time knowledge transfer. The DEP after each knowledge transfer can be seen as the DEP before knowledge transfer of the next knowledge transfer. Then, the optimal time of multiple knowledge transfers at different time points in the big data environment can be obtained. The modeling idea and method are as shown in Fig. 1.

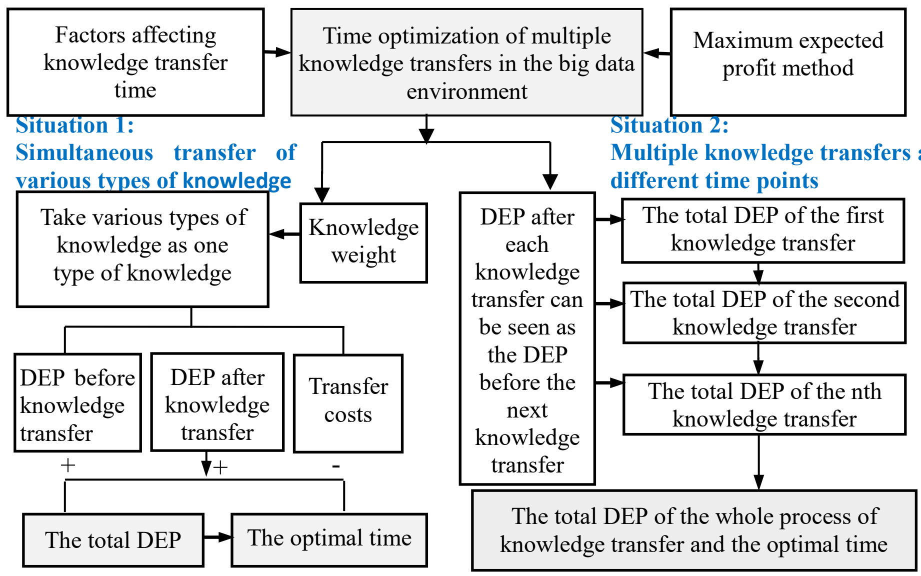

Figure 1: Model method

According to the modeling concept in Fig. 1, various types of knowledge transfers at different time points in the big data environment can be decomposed into many simultaneous knowledge transfers. Therefore, the most important thing for the time optimization of multiple knowledge transfers in the big data environment is to find the optimal time of the one-time knowledge transfer of various types of knowledge.

3 Time optimization model of multiple simultaneous knowledge transfers

3.1 Model hypotheses

This model is based on previous research. The same assumptions and variables remain unchanged as follows. The expression of an innovation network in the big data environment is $G=(V,E,BD)$. An enterprise V_i will produce only one product. The total market volume of the new product is Q, the price of the product is p, and the marginal cost in the starting period is MC. The knowledge absorption capacity is $\alpha(0<\alpha<1)$. The market share of V_i in the starting period is ϕ. The market share of V_i increases at a rate of $\theta_1(0<\theta_1<1)$ in the first L_1 periods and decreases at a rate of $\theta(0<\theta<1)$ in the other periods. The discount rate is r, the life cycle of the product is N, and N is renumbered after each knowledge transfer. For the details on assumptions, see to the research of Wu et al. [Wu, Chen and Li (2016); Wu and Zeng (2009)]. In addition, six new hypotheses are proposed:

Hypothesis 1. V_i is an enterprise in $G=(V,E,BD)$. V_i needs to transfer A types of private knowledge from other enterprises, and V_i also needs to transfer B types of big data knowledge from the big data knowledge providers. All the private knowledge and the big data knowledge will transfer simultaneously at time period T ($0 < T < N$).

Hypothesis 2. ω_{11}, $\omega_{12}, \ldots$ ω_{1A} are the weights of A types of private knowledge, and ω_{21}, $\omega_{22}, \ldots \omega_{2B}$ are the weights of B types of big data knowledge $(0 \le \omega_{11}, \omega_{12}, \cdots, \omega_{1A}, \omega_{21}, \omega_{22}, \cdots, \omega_{2B} \le 1;$ $\omega_{11} + \omega_{12} + \cdots + \omega_{1A} + \omega_{21} + \omega_{22} + \cdots + \omega_{2B} = 1)$.

Hypothesis 3. The update rate of the first type of private knowledge from another enterprise is β_{11}, the update rate of the second type of private knowledge is β_{12}, and the update rate of the *A*th type of private knowledge is β_{1A}. The update rate of the first type of big data knowledge from big data knowledge provider is β_{21}, the update rate of the second type of big data knowledge is β_{22}, and the update rate of the *B*th type of big data knowledge is β_{2B}. The update rate of all external new knowledge at time period $n = 0$ is β $(0 < \beta < 1)$.

Hypothesis 4. The fixed transfer cost of the first type of private knowledge is k_{11}, the fixed transfer cost of the second type of private knowledge is k_{12}, and the fixed transfer cost of the *A*th type of private knowledge is k_{1A}. The fixed transfer cost of the first type of big data knowledge is k_{21}, the fixed transfer cost of the second type of big data knowledge is k_{22}, and the fixed transfer cost of the *B*th type of big data knowledge is k_{2B}. All the fixed transfer costs are constants.

Hypothesis 5. $\rho(0 < \theta_1 < \rho < 1)$ is the total growth rate of the market share of V_i in the first L_2 periods immediately after V_i transfers various types of knowledge at the time period T. ρ_{11} is the growth rate of the market share of V_i in the first L_2 periods immediately after V_i only transfers the first type of private knowledge at the time period T. ρ_{12} is the growth rate of the market share of V_i in the first L_2 periods immediately after V_i only transfers the second type of private knowledge at the time period T. ρ_{1A} is the growth rate of the market share of V_i in the first L_2 periods immediately after V_i only transfers the *A*th type of private knowledge at the time period T. ρ_{21}, $\rho_{22}, \ldots \rho_{2B}$ are the respective growth rates of the market share of each type of big data knowledge after V_i only transfers each type of big data knowledge at the time period T $(0 < \theta_1 < \rho_{11}, \rho_{12}, \cdots, \rho_{1A}, \rho_{21}, \rho_{22}, \cdots, \rho_{2B} < 1)$.

Hypothesis 6. $\zeta(T)$ is the DEP of V_i before transferring new knowledge, $\xi(T)$ is the DEP of V_i received after transferring various types of new knowledge at time point T, and $K(T)$ is the knowledge transfer cost of all external new knowledge. The total DEP of V_i is denoted as $\Psi(T)$ and $\Psi(T)=\zeta(T)+\xi(T)\text{-}K(T)$.

3.2 DEP before multiple simultaneous knowledge transfers

Because there is no new knowledge before knowledge transfer, V_i produces new product using prior knowledge. From the previous hypotheses, the market share changes from growth to decay at time period $T = L_1$. Therefore, the entire life cycle of the product can be divided into two phases: $T \le L_1$ and $T > L_1$. The net profit of V_i during this period can be calculated by subtracting the total production cost from the total sales revenues. Then, the total DEP of V_i before various types of simultaneous knowledge transfers can be obtained by discounting the net profits of each phase to the starting point $n = 0$. The DEP before knowledge transfer is as shown in Eq. (1). The detailed calculation method is introduced by Wu et al. [Wu and Zeng (2009)].

$$\zeta(T)=\begin{cases} pQ\phi\sum_{n=1}^{T}(1+\theta_1)^n r^n - Q\phi MC\sum_{n=1}^{T}(1+\theta_1)^n\alpha^n r^n & T\le L_1 \\ pQ\phi\sum_{n=1}^{L_1}(1+\theta_1)^n r^n - Q\phi MC\sum_{n=1}^{L_1}(1+\theta_1)^n\alpha^n r^n + pQ\phi(1+\theta_1)^{L_1}\sum_{n=L_1+1}^{T}(1-\theta)^{n-L_1}r^n & \\ \quad - Q\phi MC(1+\theta_1)^{L_1}\sum_{n=L_1+1}^{T}(1-\theta)^{n-L_1}\alpha^n r^n & T>L_1 \end{cases} \tag{1}$$

3.3 Transfer cost of various types of knowledge

The transfer cost K is formed by the fixed transfer cost k_{fix} and the variable cost k_{var}. The fixed transfer cost k_{fix} can be calculated by the weight and the fixed transfer cost of each type of knowledge. From hypotheses 2 and 4, the fixed transfer cost of various types of knowledge can be calculated by Eq. (2).

$$k_{fix}=\sum_{j=1}^{A}\omega_{1j}k_{1j}+\sum_{k=1}^{B}\omega_{2k}k_{2k} \quad (0\le\omega_{1j},\omega_{2k}\le 1;\ \sum_{j=1}^{A}\omega_{1j}+\sum_{k=1}^{B}\omega_{2k}=1) \tag{2}$$

The variable cost k_{var} is related to the knowledge level gap between V_i and the updated rate of external new knowledge. From the modeling method, the weights of private knowledge and big data knowledge are calculated by the profit contribution rate of each type of knowledge. Thus, $\omega_{11},\omega_{12},\cdots,\omega_{1A},\omega_{21},\omega_{22},\cdots,\omega_{2B}$ can also be seen as the weight of the update rate of each type of knowledge. The update rate of all external new knowledge β can be obtained by Eq. (3).

$$\beta=\sum_{j=1}^{A}\omega_{1j}\beta_{1j}+\sum_{k=1}^{B}\omega_{2k}\beta_{2k} \quad (0\le\omega_{1j},\omega_{2k}\le 1;\ \sum_{j=1}^{A}\omega_{1j}+\sum_{k=1}^{B}\omega_{2k}=1) \tag{3}$$

From hypotheses 2-4, the variable cost can be computed by Eq. (4), where F is the coefficient of variable cost, and F a constant.

$$k_{\mathrm{var}} = F[\alpha^T - (\sum_{j=1}^{A}\omega_{1j}\beta_{1j} + \sum_{k=1}^{B}\omega_{2k}\beta_{2k})^T] \quad (0 \le \omega_{1j}, \omega_{2k} \le 1;\ \sum_{j=1}^{A}\omega_{1j} + \sum_{k=1}^{B}\omega_{2k} = 1) \tag{4}$$

After discounting the transfer cost to the starting point, the total transfer cost of various types of knowledge can be expressed as Eq. (5).

$$K(T) = [\sum_{j=1}^{A}\omega_{1j}k_{1j} + \sum_{k=1}^{B}\omega_{2k}k_{2k} + F[\alpha^T - (\sum_{j=1}^{A}\omega_{1j}\beta_{1j} + \sum_{k=1}^{B}\omega_{2k}\beta_{2k})^T]]r^T \tag{5}$$

3.4 DEP after multiple simultaneous knowledge transfers

Suppose that $\omega_{11}, \omega_{12}, \cdots, \omega_{1A}, \omega_{21}, \omega_{22}, \cdots, \omega_{2B}$ are also the weights of the growth rates of the market shares of each type of knowledge. The total growth rate of market share ρ can be calculated by Eq. (6).

$$\rho = \sum_{j=1}^{A}\omega_{1j}\rho_{1j} + \sum_{k=1}^{B}\omega_{2k}\rho_{2k} \quad (0 < \theta_1 < \rho_{1j}, \rho_{2k} < 1) \tag{6}$$

If V_i transfers new knowledge at time period T, when $T \le L_1$, the market share of V_i in time period T is $\phi(1+\theta_1)^T$. When $T > L_1$, the market share of V_i is $\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}$. After the period of time T, new knowledge began to work on the market share of V_i. From previous hypotheses and hypothesis 5, the market share of V_i will increase at a rate of ρ in the L_2 periods immediately after time period T, and it will then decay at a rate of θ. Hence, the market share of V_i in period n can be denoted as Eq. (7).

$$\lambda(n,T) = \begin{cases} \phi(1+\theta_1)^T(1+\sum_{j=1}^{A}\omega_{1j}\rho_{1j} + \sum_{k=1}^{B}\omega_{2k}\rho_{2k})^n & n \le L_2,\ T \le L_1 \\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}(1+\sum_{j=1}^{A}\omega_{1j}\rho_{1j} + \sum_{k=1}^{B}\omega_{2k}\rho_{2k})^n & n \le L_2,\ T > L_1 \\ \phi(1+\theta_1)^T(1+\sum_{j=1}^{A}\omega_{1j}\rho_{1j} + \sum_{k=1}^{B}\omega_{2k}\rho_{2k})^n(1-\theta)^{n-L_2} & n > L_2,\ T \le L_1 \\ \phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}(1+\sum_{j=1}^{A}\omega_{1j}\rho_{1j} + \sum_{k=1}^{B}\omega_{2k}\rho_{2k})^{L_2}(1-\theta)^{n-L_2} & n > L_2,\ T > L_1 \end{cases} \tag{7}$$

From hypothesis 3, the update rate of all external new knowledge at time period $n = 0$ is β. Considering the time cumulative effect, the external new knowledge at time period T has been updated by β^T, which can make the marginal cost of V_i at time period T reduce to $MC\beta^T$. The knowledge absorption capacity of V_i is α. Then, the marginal cost of V_i at time period T will become $MC\beta^T\alpha^n$. By replacing β^T with Eq. (3), the marginal cost at time period T of V_i can be calculated by Eq. (8).

$$MC\beta^T\alpha^n = MC(\sum_{j=1}^{A}\omega_{1j}\beta_{1j} + \sum_{k=1}^{B}\omega_{2k}\beta_{2k})^T\alpha^n \tag{8}$$

The total production cost at time period n after knowledge transfer is $Q\lambda(n,T)MC(\sum_{j=1}^{A}\omega_{1j}\beta_{1j} + \sum_{k=1}^{B}\omega_{2k}\beta_{2k})^T\alpha^n$. By subtracting the total production cost from the sales revenue $pQ\lambda(n,T)$, the profit at time period n after knowledge transfer can be obtained by Eq. (9)

$$\Pi^* = pQ\lambda(n,T) - Q\lambda(n,T)MC(\sum_{j=1}^{A}\omega_{1j}\beta_{1j} + \sum_{k=1}^{B}\omega_{2k}\beta_{2k})^T\alpha^n \tag{9}$$

Through discounting the profits in period n to the starting point by multiplying Equation (9) with $r^T r^n$ and summing up all the discounted profits in the life cycle N, the DEP after knowledge transfer is as shown in Eq. (10)

$$\xi(T) = r^T\sum_{n=1}^{N}(pQ\lambda(n,T) - Q\lambda(n,T)MC(\sum_{j=1}^{A}\omega_{1j}\beta_{1j} + \sum_{k=1}^{B}\omega_{2k}\beta_{2k})^T\alpha^n)r^n \tag{10}$$

By using Eqs. (7) and (10), the expected profits after knowledge transfer can be expressed as Eq. (11)

$$\xi(T) = \begin{cases} pQ\phi(1+\theta_1)^T r^T \sum_{n=1}^{L_2}(1+\sum_{j=1}^{A}\omega_{1j}\rho_{1j} + \sum_{k=1}^{B}\omega_{2k}\rho_{2k})^n r^n \\ -MCQ\phi(1+\theta_1)^T r^T (\sum_{j=1}^{A}\omega_{1j}\beta_{1j} + \sum_{k=1}^{B}\omega_{2k}\beta_{2k})^T \sum_{n=1}^{L_2}(1+\sum_{j=1}^{A}\omega_{1j}\rho_{1j} + \sum_{k=1}^{B}\omega_{2k}\rho_{2k})^n \alpha^n r^n \\ +pQ\phi(1+\theta_1)^T (1+\sum_{j=1}^{A}\omega_{1j}\rho_{1j} + \sum_{k=1}^{B}\omega_{2k}\rho_{2k})^{L_2} r^T \sum_{n=L+1}^{N}(1-\theta)^{n-L_2} r^n \\ -MCQ\phi(1+\theta_1)^T r^T (\sum_{j=1}^{A}\omega_{1j}\beta_{1j} + \sum_{k=1}^{B}\omega_{2k}\beta_{2k})^T (1+\sum_{j=1}^{A}\omega_{1j}\rho_{1j} + \sum_{k=1}^{B}\omega_{2k}\rho_{2k})^{L_2} \sum_{n=L+1}^{N}(1-\theta)^{n-L_2}\alpha^n r^n & T \le L_1 \\ pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1} r^T \sum_{n=1}^{L_2}(1+\sum_{j=1}^{A}\omega_{1j}\rho_{1j} + \sum_{k=1}^{B}\omega_{2k}\rho_{2k})^n r^n \\ -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}\beta^T r^T \sum_{n=1}^{L_2}(1+\sum_{j=1}^{A}\omega_{1j}\rho_{1j} + \sum_{k=1}^{B}\omega_{2k}\rho_{2k})^n \alpha^n r^n \\ +pQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1}(1+\sum_{j=1}^{A}\omega_{1j}\rho_{1j} + \sum_{k=1}^{B}\omega_{2k}\rho_{2k})^{L_2} r^T \sum_{n=L+1}^{N}(1-\theta)^{n-L_2} r^n \\ -MCQ\phi(1+\theta_1)^{L_1}(1-\theta)^{T-L_1} r^T (\sum_{j=1}^{A}\omega_{1j}\beta_{1j} + \sum_{k=1}^{B}\omega_{2k}\beta_{2k})^T (1+\sum_{j=1}^{A}\omega_{1j}\rho_{1j} + \sum_{k=1}^{B}\omega_{2k}\rho_{2k})^{L_2} \sum_{n=L+1}^{N}(1-\theta)^{n-L_2}\alpha^n r^n & T > L_1 \end{cases} \tag{11}$$

3.5 Total DEP model

From the modeling idea and methods, the time optimization problem of multiple simultaneous knowledge transfer of various types of knowledge must find the maximum of the total DEP $\Psi(T)$ of V_i for the given parameters. Therefore, the optimization model of multiple simultaneous knowledge transfer can be expressed as Eq. (12).

$$\max\Psi(T)=\max(\zeta(T)+\xi(T)-K(T)) \tag{12}$$

4 Simulation experiments

4.1 Model solution

It can be seen from Eq. (12) that $\Psi(T)$ is a piecewise continuous differential function of T. Therefore, $\Psi(T)$ can reach its maximum in a closed interval $0 \le T \le N$, and the maximum profits in the life cycle of the product can be found. Then, the optimal time of multiple knowledge transfers can be obtained.

MATLAB 7.0 has been used to compile a program that considers the power of the numerical calculation and simulation functions. Some simulation experiments of actual situations could be conducted by adjusting the model's parameters.

4.2 Simulation experiments

4.2.1 Common parameter setting and simulation

To simulate multiple knowledge transfer in the big data environment, several common parameters are chosen for testing. The values of some common parameters are set the same as those of Wu et al. [Wu, Chen and Li (2016)] and are as shown in Tab. 1.

Table 1: Values of common parameter

Parameter	Q	p	MC	θ_1	θ	ϕ	L_1	L_2	α	N	F	r
Value	1000	60	40	3%	3%	8%	3	5	95%	10	1000	0.9

When $A=1, B=1$, it means that V_i will simultaneously transfer one type of private knowledge and one type of big data knowledge. Let $k_{11}=300$, $k_{21}=80$, $\rho_{11}=6\%$, $\rho_{21}=8\%$, $\beta_{11}=88\%$, $\beta_{21}=88\%$, $\omega_{11}=0.6$ and $\omega_{21}=0.4$, which means that 60 percent of knowledge is private knowledge, and 40 percent of other knowledge is big data knowledge. Tab. 2 and Fig. 2 show the experimental results of the DEPs before knowledge transfer (DEPb), the DEPs after knowledge transfer (DEPa), the transfer costs, and the total DEPs. According to the model's solution, the optimal time of knowledge transfer is $T=5$, and the total DEPs are the same as those of Wu et al. [Wu, Chen and Li (2016)]. Therefore, the model is valid.

Table 2: Model validation with $\omega_{11} = 0.6, \omega_{21} = 0.4$

Period	DEP before transfer	DEP after transfer	Transfer cost	Total DEP
1	1632	17245	254	18622
2	3275	17645	275	20644
3	4913	17710	283	22340
4	6438	16501	280	22659
5	7849	15204	270	22782
6	9146	13887	257	22776
7	10333	12594	240	22688
8	14415	11357	222	22550
9	12396	10193	204	22385
10	13284	9112	186	22211

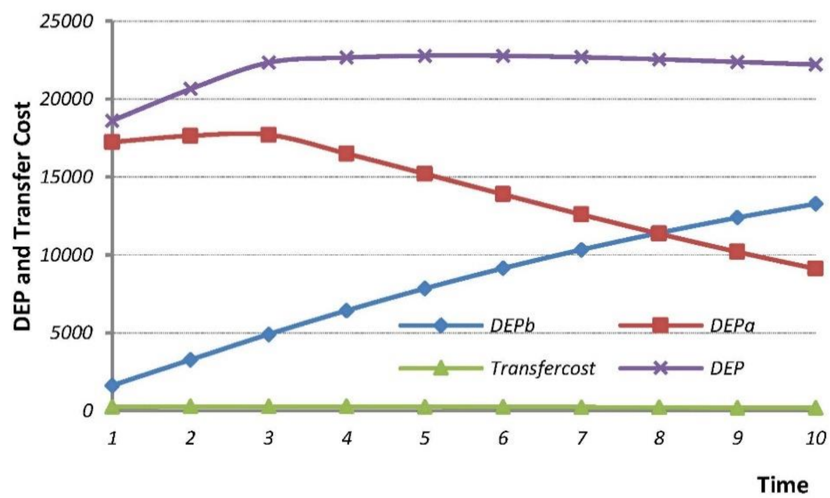

Figure 2: Changes in DEPs and transfer costs with $\omega_{11} = 0.6, \omega_{21} = 0.4$

Let $k_{11} = 300$, $k_{21} = 80$, $\rho_{11} = 6\%$, $\rho_{21} = 8\%$, $\beta_{11} = 88\%$, $\beta_{21} = 88\%$, $\omega_{11} = 0.4$ and $\omega_{21} = 0.6$. This means that 40 percent of knowledge is private knowledge and 60 percent of other knowledge is big data knowledge. Tab. 3 and Fig. 3 show the experimental results of the DEPb, the DEPa, the transfer costs, and the total DEPs of V_i. By comparing the results in Tab. 3 with those in Tab. 2, it can be seen that the total DEPs increase and the transfer costs decrease with the increase in the weight of big data knowledge. The reason is that the fixed costs of big data knowledge are much lower, and the big data knowledge can help enterprises enhance productivity by guiding decisions, trimming costs and increasing the quality of products and services [McGuire, Manyika and

Chui (2012); Lohr (2012)]. Therefore, the simulation results are in accordance with the actual situation, and the model is valid.

Table 3: Model validation with $\omega_{11} = 0.4, \omega_{21} = 0.6$

Period	DEP before transfer	DEP after transfer	Transfer cost	Total DEP
1	1632	17497	214	18914
2	3275	17901	240	20935
3	4913	17965	251	22627
4	6438	16737	251	22924
5	7849	15421	244	23026
6	9146	14084	233	22998
7	10333	12773	219	22888
8	14415	11518	203	22730
9	12396	10337	187	22547
10	13284	9241	170	22355

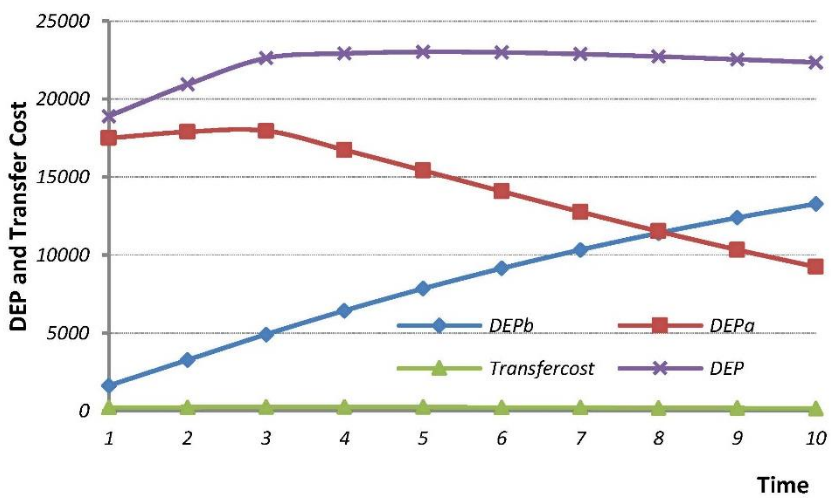

Figure 3: Changes of DEPs and transfer costs when $\omega_{11} = 0.4, \omega_{21} = 0.6$

4.2.2 Simulation of with $A = 2, B = 1$

When $A = 2, B = 1$, it means that V_i will simultaneously transfer two types of private knowledge and one type of big data knowledge. To compare the results with those in Tab. 2 and Fig. 2, the weights of the two types of private knowledge are set at 0.3. That means that two types of private knowledge account for 60 percent, and big data knowledge accounts for 40%, which is the same as that of Tab. 2 and Fig. 2. The values of several new parameters are presented in Tab. 4. The values of the parameters in Tab. 4 show that the transfer costs and efficiency of one type of private knowledge are all increased.

Table 4: Parameter values when A=2, B=1

Parameter	ω_{11}	ω_{12}	ω_{21}	k_{11}	k_{12}	k_{21}	ρ_{11}	ρ_{12}	ρ_{21}	β_{11}	β_{12}	β_{21}
Value	0.3	0.3	0.4	300	320	80	6%	12%	8%	88%	80%	88%

Tab. 5 and Fig. 4 show the changes of DEPb, DEPa, transfer costs and the total DEPs of V_i. The optimal time for knowledge transfer is $T=4$. When comparing the experimental results with those in Tab. 2 and Fig. 2, despite the increase in the transfer costs of one type of private knowledge, the total DEPs increase with the efficiency of the private knowledge. The optimal time for knowledge transfer changes from $T=5$ to $T=4$. The reason is that private knowledge is usually the core patent knowledge, which can greatly improve the technology innovation performance of the enterprise. The more efficient the private knowledge is, the greater the total DEP, and the earlier that knowledge transfer occurs.

Table 5: DEPs and transfer costs with A=2, B=1

Period	DEP before transfer	DEP after transfer	Transfer cost	Total DEP
1	1632	18837	281	20188
2	3275	19517	314	22478
3	4913	19723	327	24309
4	6438	18437	325	24550
5	7849	17006	314	24541
6	9146	15527	297	24376
7	10333	14064	277	24120
8	14415	12658	255	23817
9	12396	11334	233	23497
10	13284	10107	211	23180

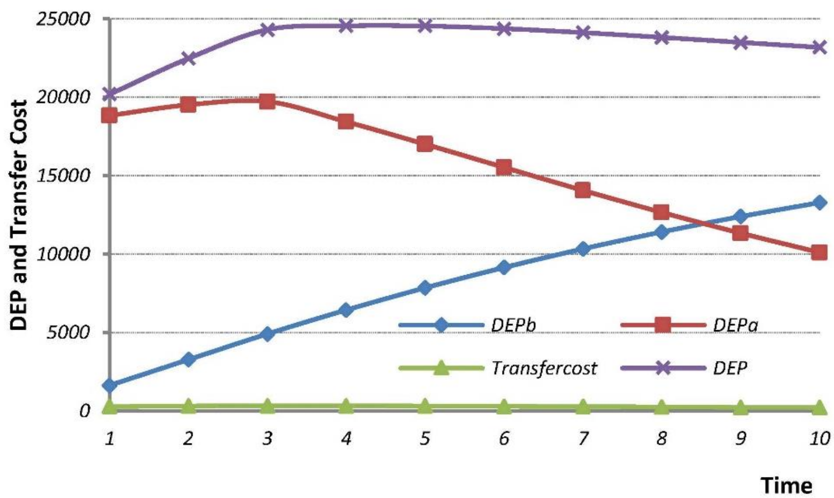

Figure 4: Changes of DEPs and transfer costs when A=2, B=1

4.2.3 Simulation of with $A=2, B=1$

When $A=1, B=2$, it means that V_i will simultaneously transfer one type of private knowledge and two types of big data knowledge. The values of several new parameters are presented in Tab. 6. As seen from Tab. 6, the proportion of the two types of big data knowledge account for 60 percent, and the private knowledge accounts for 40 percent, which is the same as that of Tab. 3 and Fig. 3. Furthermore, the parameter values in Tab. 6 also show that the transfer costs and efficiency of one type of big data knowledge are reduced.

Table 6: Parameter values when A=1, B=2

Parameter	ω_{11}	ω_{21}	ω_{21}	k_{11}	k_{21}	k_{22}	ρ_{11}	ρ_{21}	ρ_{22}	β_{11}	β_{21}	β_{22}
Value	0.4	0.3	0.3	300	80	70	6%	8%	6%	88%	88%	90%

Tab. 7 and Fig. 5 show the experimental results of DEPb, DEPa, transfer costs and the total DEPs of V_i . The optimal time for knowledge transfer is $T=6$. Comparing the experimental results with those in Tab. 3 and Fig. 3, although the transfer costs of one type of big data knowledge are reduced, the total DEPs have also declined. The optimal time for knowledge transfer changes from $T=5$ to $T=6$. The reason is that the fixed costs of big data knowledge are extremely low, and the marginal costs are almost negligible. The efficiency of big data knowledge having lower transfer costs is limited to the profits growth of the enterprise. If the expected profits are not large enough, the enterprise will delay knowledge transfer.

Table 7: DEP and transfer cost with A=1, B=2

Period	DEP before transfer	DEP after transfer	Transfer cost	Total DEP
1	1632	17019	206	18444
2	3275	17353	229	20398
3	4913	17381	238	22055
4	6438	16175	238	22375
5	7849	14895	232	22512
6	9146	13603	221	22528
7	10333	12338	208	22464
8	14415	11130	193	22351
9	12396	9994	178	22212
10	13284	8939	162	22060

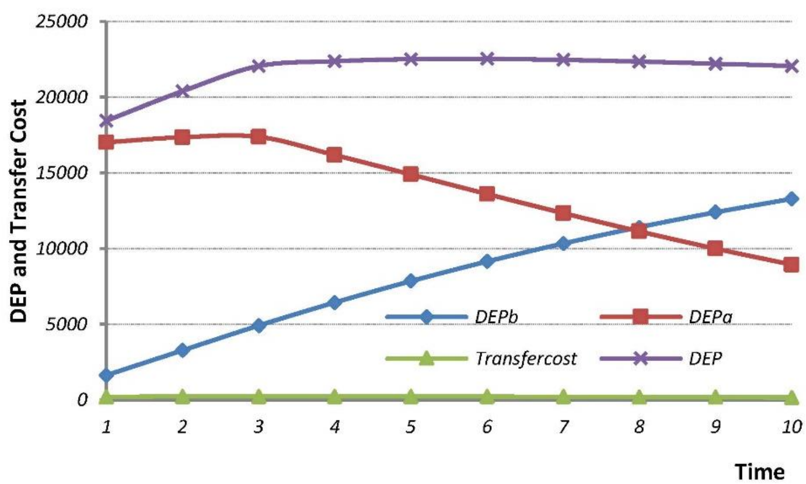

Figure 5: Changes of DEPs and transfer costs when A=1, B=2

5 Conclusion

This paper analyzed the time optimization problem of multiple knowledge transfer in the big data environment. Based on the analysis of the complex process and influential factors of multiple knowledge transfers in the big data environment, the activities of multiple knowledge transfer are divided into two categories. One is the simultaneous transfers of various types of knowledge, and the other one is that multiple knowledge transfers of various types of knowledge at different time points. Taking into consideration the influential factors, such as the knowledge type, knowledge structure, knowledge absorptive capacity, knowledge update rate, discount rate, market share, profit contribution of each type of knowledge, transfer cost, product life cycle and so on, time optimization models of multiple knowledge transfers are presented by maximizing the total DEP of an enterprise. Some simulation experiments have been performed to verify the validity of models, and the models can help enterprises determine the optimal time of complex multiple knowledge transfers in the big data environment.

The proposed models in this paper have several limitations, and further research is needed. Multiple knowledge transfers at different time points in the big data environment are just decomposed into many times of simultaneous knowledge transfers. However, the optimal time for the first knowledge transfer usually affects the second knowledge transfer in real-world circumstances if the time interval is not too long. Enterprises have to comprehensively determine the optimal time for multiple knowledge transfers. Compared with the profits, the transfer costs are set too low, especially the transfer costs of private knowledge. Therefore, the transfer costs should be adjusted to discover their impact on the total DEPs. Additionally, our assumptions that the enterprise only produces one product and the price remains flat can be relaxed to accommodate more realistic circumstances.

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