Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org

Volume 25, Issues 4, pp. 2770–2782, DOI 10.12694/scpe.v25i4.2815

SOCIAL MEDIA AND CLOUD COMPUTING IMPACT ON HUMAN RESOURCE MANAGEMENT IN MULTINATIONAL ENTERPRISES

TIANLIANG DU*

Abstract. To address the issues of high storage costs for human resource data, resource management of human resource systems, and employee social interaction in human resource management, this study proposes an adaptive intelligent HR data placement strategy based on genetic algorithms. Additionally, a fitness model and an employee social interaction model are presented. The fitness model utilizes genetic algorithms to optimize data storage strategy and server load balancing, resulting in reduced overall costs and efficient resource utilization. This is achieved by comprehensively considering data transmission latency and storage costs. The employee social interaction model analyzes social media blog post topics and employee ranks, and employs a co-training method to predict employee interactions. The experimental results indicated that the placement strategy can improve the HR data transfer by nearly 50% and effectively reduce the standard deviation of server load by about 10-15%. The accuracy, recall, F1 value, and precision of the employee social interaction model were 77.89%, 63.97%, 70.32%, and 71.78%, respectively. The proposed strategy and model demonstrated higher accuracy and robustness in predicting and analyzing employee social interactions, thus providing more reliable decision support for human resource management.

Key words: Social media; Cloud computing; Human resources; Employee interaction; Multinational enterprises

1. Introduction. Under globalization and matization, multinational enterprises competitiveness depends on their comprehensive capabilities, including their ability to recruit, train, develop and retain human resources worldwide. These capabilities are mainly reflected through systematic transnational human resource management methods and business levels. Driven by computer technology, artificial intelligence algorithms, network computing, data mining and other technologies have been widely used in transnational human resource management [1-3]. The interaction among employees in multinational enterprises directly affects their work efficiency. Negative interaction can have a detrimental effect on human resource management and global business development. Corporate social networks have important value in improving employee satisfaction and enhancing global teamwork. At present, there is little research on corporate social media application in transnational human resource management, which needs to be further discussed [4-6]. The cloud computing platform provides on-demand network storage computing resource services. Meanwhile, the impact of social media and cloud computing on human resource management of multinational enterprises helps to enhance the competitiveness of enterprises. Therefore, studying the application of social media and cloud computing is important in transnational human resource management to promote multinational enterprises development [7-9]. This study includes four parts, the first part is a summary of the study and the analysis of related research, the second part is to design the application research methods of corporate social media in transnational human resource management, the third part is to analyze the data, and the fourth part is to draw the research conclusion.

2. Related works. In recent years, the research of enterprise social network is deepening. Li team proposed an integrated research framework, presenting the future trend of ESM research. The research carried out quantitative analysis and visualization of ESM research, which had certain originality and value [10]. Liang team built a research model to explore the impact of the use of public and private social media platforms under different motivations on employees' job satisfaction and work efficiency. The research results showed that public social media had a positive impact on employee job satisfaction [11]. Luqman a team used the moderating focus theory (RFT) to propose the moderating effect of employees' promoting and preventing

*E-commerce Logistics Department, Zhengzhou Vocational College of Automobile Engineering, Zhengzhou 450000, China (dutianliang520@163.com)

focus on these relationships. The results showed that interruption load and psychological change mediated the relationship between ESM use and fatigue and creativity respectively [12]. Laitinen team discussed various factors for employees to share information on corporate social media platforms. It tried to comprehensively describe the factors that shaped employees' decision on corporate social media. The study found that employees' information sharing decisions were influenced by privacy management principles [13].

Additionally, research on human resources is also deepening. Vrontis team conducted a comprehensive analysis of international business, general management and information management. The research results showed that intelligent automation technology provided a new method for managing employees and improving company performance [14]. Ngoc Su D team revealed the beneficial practice of human resource flexibility construction implemented by enterprises before, during and after the closure. The research results showed that it was of great significance to maintain the tourism labor force and enhance the organizational flexibility [15]. Guest D E team took the signaling theory as a framework to integrate the two attribution methods in human resource management and found that there was a positive correlation between the strong HR signal and the HR attribution and attitude of employees as receivers [16]. Vinoth S and their team investigated and evaluated the most significant network security and data security risks in the cloud system. While virtualization was promoted as a solution to current security issues, improper virtualization could have a negative impact on the network system's security by adding additional software. Additionally, the data center hub is connected to the server through software. If there was a problem, it may have a serious impact on security. Since users had no control over cloud resources, they must rely on the trust mechanism [17]. Sandhu A K team discussed the definition, classification and characteristics of big data, as well as various cloud services. At the same time, it made a comparative analysis of big data frameworks based on cloud. [18].

It can be concluded that the research in recent years has focused on the motivation and effect of social media use and the factors of employee information sharing. In addition, the application of cloud computing and big data has also played an important role in human resource management, such as the application of intelligent automation technology, and the research on network security and data security risks in cloud systems. The innovation of this study is mainly reflected in integrating the influencing factors of social media and cloud computing, and studying their impact on human resource management of multinational enterprises from a new perspective. This not only broadens the research perspective, but also provides new human resource management strategies for multinational enterprises.

3. Design of interactive model of employee interaction management in human resource management of Multinational Enterprises. An adaptive intelligent data placement strategy based on genetic algorithm is proposed. This strategy can help social network service providers improve economic benefits. In addition, aiming at the problem of server resource management in social network environment, a fitness model is proposed to achieve load balancing. Finally, the interaction model design of enterprise social network is discussed in detail. By integrating these three aspects, an effective model for enterprise social network interaction can be built. This model provides a new solution to the problems of data storage costs, server resource management, and enterprise social network interaction in online social networks.

3.1. Design of social cloud computing data placement model in human resource management of Multinational Enterprises. The development of social network provides new possibilities for human resource management of multinational companies. Social networks can help multinational companies better understand employees' needs and expectations, and improve employees' participation and job satisfaction. However, the management and analysis of social network data is a complex process, which requires a lot of computing resources and storage space. Adaptive intelligent data placement strategy based on genetic algorithm can help multinational companies effectively manage social network data, improve the efficiency of data processing and reduce the cost of data storage.

An adaptive intelligent data placement strategy based on genetic algorithm is proposed. The research is based on genetic algorithm when designing intelligent data placement algorithm. At the start of the algorithm, an initial population is randomly generated. Then, through the principles of survival of the fittest and natural selection, individuals are selected, crossed over, and mutated to create the next generation. This process is repeated until a better solution is obtained. The crossover operation is shown in Fig. 3.1.

Social network services need a solution that can not only ensure users to access data within a tolerable

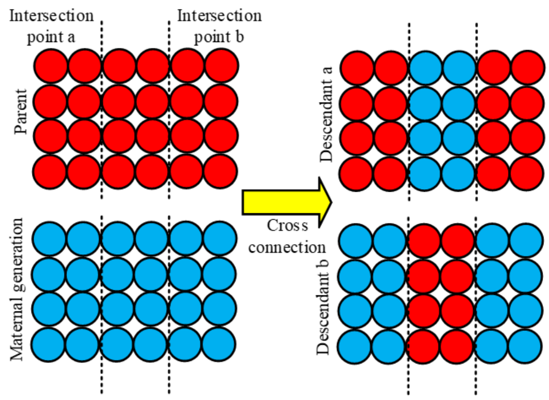


Fig. 3.1: Cross operation

delay time, but also reduce costs as much as possible and improve their own economic benefits. The proposed data placement strategy based on genetic algorithm fully considers the above factors. First of all, suppose that each user has a master copy located in the nearest master data center from where they are located. Users access their own data from the master data center and their friends' data from the nearest data center with copies of their friends' data. Then, genetic algorithm is used to find the optimal data placement scheme. The goal of the research is to reduce the storage cost as much as possible within the delay time of no more than 250ms, so as to realize the economic benefits of social network service providers. The user's master data center is shown in formula (3.1).

$$x_{ij} = \begin{cases} 1 & \text{User z's data is stored in data center y} \\ 0 & Other \end{cases} \tag{3.1}$$

The total storage cost is shown in formula (3.2).

$$Cost = \sum_{i=1}^{N} StorageCost_i \tag{3.2}$$

$StorageCost_i$ is calculated in formula (3.3).

$$StorageCost_i = UnitStoragePrice \times StoredDataSize_i \times (R_i + 1) \tag{3.3}$$

$UnitStoragePrice$ represents the storage cost of 1GB of data in cloud storage for one month. $StoredDataSize_i$ indicates the size of user data volume, and R_i indicates the volume of replicas stored in other data centers except the primary replica. The user's access delay time is expressed as a linear function, as shown in formula (3.4).

$$\frac{\delta_{(round_{trip_{time}})}}{\delta_{(dis\tan ce)}} \approx 0.02ms/km \tag{3.4}$$

$round_{trrip_{time}}$ represents the delay time when the user accesses and $distance$is the distance between the user and the data center. Assuming that there is a 20ms delay between the user and the master data center, the delay time formula is shown in formula (3.5).

$$latency\,(ms) = \begin{cases} 20 & \text{Delay between users and the main data center} \\ 0.02 \times dia\tan ce + 5 & Other \end{cases} \tag{3.5}$$

$latency$ indicates the delay time for users to access the data center. The $latency_i$ limiting conditions are shown in formula (3.6).

$$latency_i \leq DesiredLatency \tag{3.6}$$

Table 3.1: Genetic algorithm initialization phase operation

Node number	1	And	4039
Node status	0	And	1
Node status	1	And	0
Node status	0	And	0
Node status	1	And	0
Node status	0	And	1
Node status	0	And	1
Node status	1	And	0
Node status	1	And	1
Node status	0	And	1
Node status	1	And	0

$latency_i$ is the average delay time, $DesiredLatency$ is the longest delay time allowed by the user. In the initialization phase of the algorithm, an adaptive population initialization method is used. First, initialize the data center of all users randomly. Then, a certain proportion of users are randomly selected from all users. These users need to meet the delay requirement of no more than 250ms during initialization, while other users who do not need to meet the delay requirement can be initialized randomly. Next, initialize each user separately. For users who need to meet the delay requirements, place copies of their data in the data center where their friends are located. For users who do not need to meet the delay requirements, the storage location of their data copies will be randomly initialized. The initialization operation is shown in Table 3.1.

In the iterative process of the algorithm, the crossover and mutation operations are used to generate new solutions, and the fitness function is used to evaluate the quality of the solutions. The fitness function used includes data transmission delay time and storage cost. In order to solve the problem of load balancing in online social network system, a fitness model is proposed to achieve load balancing. The standard deviation is used to express the dispersion degree between the number of replica storage and the average value in the server. In the social network environment, the average load and load balancing standard deviation of servers in the same cloud data center can be calculated by formula. The average server load in the same cloud data center is shown in formula (3.7).

$$AL = \frac{\sum_{i=1}^{m} RNum_i}{m} \tag{3.7}$$

$RNum_i$ indicates the number of replica storage in the server and $m$is the number of data centers. The standard deviation of load balancing is shown in formula (3.8).

$$SL = \frac{\sqrt{\sum_{i=1}^{m} (RNum_i - AL)^2}}{m} \tag{3.8}$$

In the social network environment, combined with the load balancing index of the server, the index function of the load balancing fitness model is proposed. The function consists of two parts. The first half calculates the data transmission volume between multiple servers, and the second half calculates the load balancing standard deviation of servers. The objective function of the load balancing fitness model is shown in formula (3.9).

$$Fit = Traffic_{total}^{\lambda} + SL^{\gamma} \tag{3.9}$$

$Traffic_{total}^{\lambda}$ represents the total amount of data transmitted. λ indicates the data transmission scale and$\gamma$is the impact factor of load balancing standard deviation. In order to realize this model, an adaptive multi-objective load balancing intelligent optimization algorithm based on genetic algorithm is proposed. This algorithm can not only optimize the data storage cost and the amount of data transmission of the server, but also improve the load balancing problem of the server to the maximum extent on the basis of meeting the requirements of user delay time. The algorithm flow is shown in Fig. 3.2.

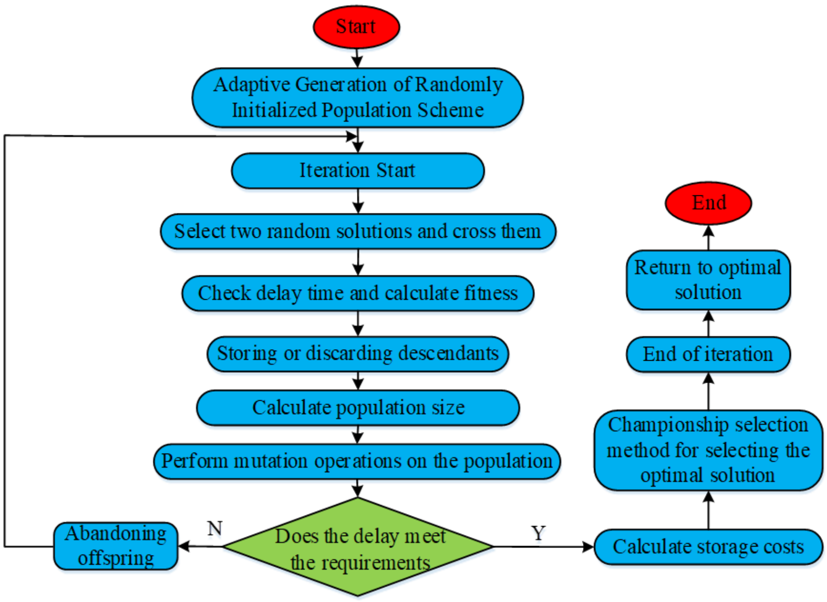


Fig. 3.2: Improve algorithm process

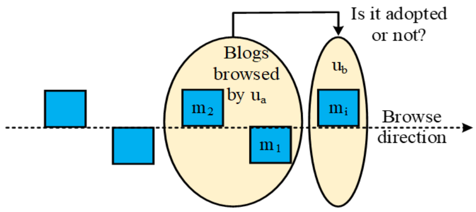


Fig. 3.3: Interactive scenes

3.2. Design of social network interaction model in human resource management of Multinational Enterprises.. As multinational companies may have different business in different countries and regions, employees' cultural backgrounds, values and working habits, it is necessary for companies to adopt more flexible and diversified strategies in human resource management. In this context, the use of social networks has become an important tool of human resource management of multinational companies. The interaction model design of enterprise social network is a complex process, which needs to consider many aspects. First, when an employee in the enterprise's social network posts a new blog post, the blog post will be immediately displayed to other employees. Blog posts in corporate social networks are displayed on employees' reading screens in chronological order, with the latest posts appearing first. Employees can browse older posts in descending chronological order through the drop-down menu. The Interaction scenario is shown in Fig. 3.3.

To solve the calculation problem of blog forwarding possibility, it is necessary to build a model. The model uses the company's personnel information to mark the rank of employees in the social network, which is called the employee rank generation module. Secondly, an LDA model must be used to extract blog topics, that is, blog topic extraction plate. Then, according to the extracted topics, the method of collaborative training is used to classify the blog posts, that is, the blog classification section. Then, statistical model learning is

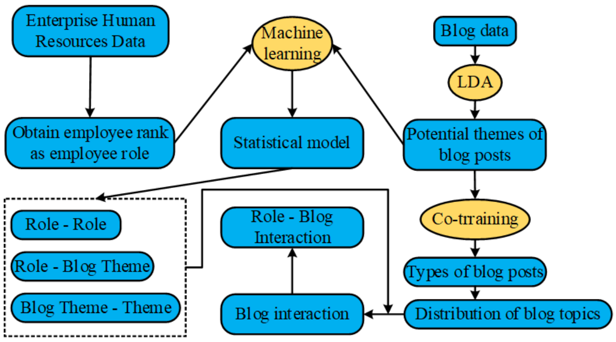


Fig. 3.4: Interactive model

conducted based on the results of employee rank and blog topic, that is, statistical model learning module. Finally, based on the results of blog classification and statistical model learning, the interaction between blog posts and employees can be inferred. This part is called interaction inference module. The interaction model is shown in Fig. 3.4.

The model is based on three interaction scenarios: the interaction between employees and blog posts, the interaction between employers and employees, and the interaction between blog posts and blog posts. The first is employee rank employee rank interaction. By inferring the interaction between different ranks, it can be inferred how the rank of the blog author affects whether employees adopt the blog. The rank interaction formula is shown in formula (3.10).

$$\Delta\left(u_a, u_b\right)=\sum_i \sum_j \Delta_{role}\left(r_i, r_j\right) \tag{3.10}$$

$\Delta role\left(r_i, r_j\right)$ represents the influence between different ranks. The second is the blog topic blog topic interaction. Each blog post is distributed on multiple topics. The topic distribution of each blog post is extracted by LDA Algorithm, and the interaction between different topics is inferred. The blog blog interaction formula is shown in formula (3.11).

$$\Lambda\left(m_i, m_k\right)=\sum_a \sum_b \theta_{i,a} \Lambda_{topic}\left(t_a, t_b\right) \theta_{k,b} \tag{3.11}$$

$\theta_{i,a}$ indicates the probability that a blog post is subordinate to the subject and $\Lambda_{topic}\left(t_a, t_b\right)$is the impact between topics. Finally, it is the interaction between employee rank and blog topic. By creating a matrix to illustrate the relationship between employee rank and blog topic, it is possible to infer how employee rank affects blog topic selection. The rank blog interaction formula is shown in formula (3.12).

$$\Omega\left(u_a, m_i\right)=\sum_j \sum_b \Omega_{topic}^{role}\left(r_j, r_b\right) \theta_{i,b} \tag{3.12}$$

Ω_{topic}^{role} indicates the interaction between employees and blog posts. The maximum likelihood function is shown in formula (3.13).

$$L\left(\Omega_{topic}^{role}, \Delta_{role}, \Delta_{topic}\right)=\sum_{i=1}^n\left(y_i \log \pi\left(x_i\right)+\left(1-y_i\right) \log \left(1-\pi\left(x_i\right)\right)\right) \tag{3.13}$$

$\pi\left(x_i\right)$ indicates the probability that employees will use blog posts. The principle of topic model is shown in Fig. 3.5.

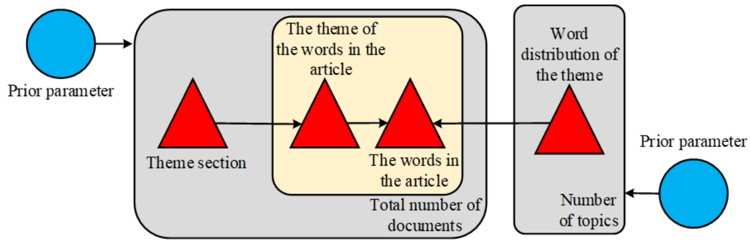


Fig. 3.5: Principle of topic model interactive model

In the design of blog classification, it is necessary to manually label part of the blog as the initial training set, and then classify the unlabeled test set through two classifiers. If the prediction results of the two classifiers are consistent, the blog will be classified into the labeled training set. After iterating repeatedly, each iteration moves some blog posts to the training set. When enough blog posts are marked, the blog category blog category interaction and employee rank blog category interaction can be obtained. Blog category - the interaction formula of blog category is shown in formula (3.14).

$$\Lambda_{cate.}\left(c_i, c_k\right) = \sum_a \sum_b \varphi_{i,a} \Lambda_{topic}\left(t_a, t_b\right) \varphi_{k,b} \tag{3.14}$$

$\varphi_{i,a}$ is the distribution of potential topics. The interactive formula of employee rank blog category is shown in formula (3.15).

$$\Omega^{role}_{cate.}\left(r_i, c_j\right) = \sum_b \Omega^{role}_{topic}\left(r_j, r_b\right) \varphi_{k,b} \tag{3.15}$$

In general, the design of enterprise social network interaction model mainly includes the construction of model framework, the design of three kinds of interaction methods and the classification of blog posts. The construction of model framework is the foundation, the design of three interactive ways is the core, and the classification of blog posts is the key. Only by integrating these three aspects can an effective interactive model of enterprise social networks be built.

4. Testing of social network data placement and interaction model under human resource management of multinational enterprises. This study designed two experiments to test the performance of data placement model and interaction model of enterprise social network. The first test recorded the changes of data transmission volume, server storage load, storage cost and other indicators. According to the experimental results, the optimization effect and performance of the data placement model are verified and analyzed. The second experiment uses the enterprise social network interaction model for experimental design, and then evaluates the relationship between model performance and blog interaction. The dataset used for both experiments was derived from the internal social networking platform of a multinational company. It covered detailed social interaction records over a one-year period and included interaction data for about 10,000 employees. The dataset contained a total of about 200,000 blog posts, as well as associated commenting, liking, and sharing behaviors. The characteristics of the data include the employee's department, position level, type of interaction (e.g., commenting, liking, sharing), time of blog posting, and content category. The data is transparent and does not compromise personal privacy.

4.1. Testing of social network data placement model under human resource management of Multinational Enterprises. To test the performance effect of the social network data placement model, the study set the number of data centers to 10, the total number of users to 4039, the average amount of data generated by each user per month to 27MB, the cost of storing the data to \$0.125 per GB per month, and the latency requirement to no more than 250ms. The study tested variables of 50%, 70%, 90%, and 99% for users

Table 4.1: Parameter settings

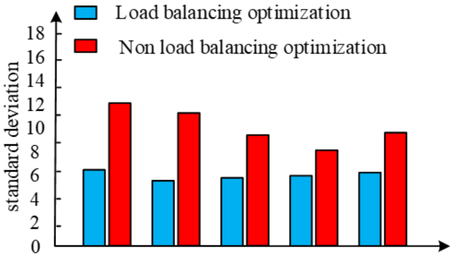
Parameter type	Numerical setting
Number of data centers	10
User (n)	4039
Monthly storage cost of 1GB of data ($)	0.125
Monthly data volume per user (MB)	27
Delay time requirement (MS)	250
Proportion of users who meet delay requirements (%)	50, 70, 90, 99
Population size	30
Crossover probability (%)	80
Mutation probability (%)	10
Iterations	50
Number of servers per data center	10-100
Storage capacity of the server $()\lambda$	64
The influencing factors of data transmission volume (a)	(0, 1)
Factors affecting the standard deviation of load balancing $()\gamma$	$(, 1)\lambda$

meeting the latency requirement. Evaluation metrics included data transfer volume variation, server storage load, and storage cost. Analyzing these metrics allowed for further conclusions on the effectiveness of the data placement model in reducing data transfer between data centers and optimizing storage costs. Parameter settings are shown in Table 4.1.

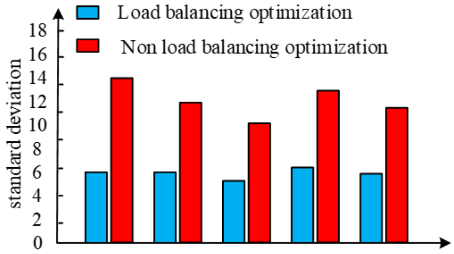
The parameter setting of intelligent optimization algorithm in social networks covers 14 aspects. These parameters are set to optimize the load balancing of social networks, so as to improve the user experience and system performance. The load comparison is shown in Fig. 4.1.

As shown in Fig. 4.1, the data transmission volume obtained by the optimization method is significantly higher than that under non-minimum ratio at any ratio, indicating that the method is effective in optimizing the data transmission volume. On this basis, 50%, 70%, 90%, 99% and 64% are studied in a single data center. The experimental results show that under the same experimental conditions, the storage load of the server is significantly reduced no matter what proportion is used. The storage cost changes with the number of iterations, as shown in Fig. 4.2.

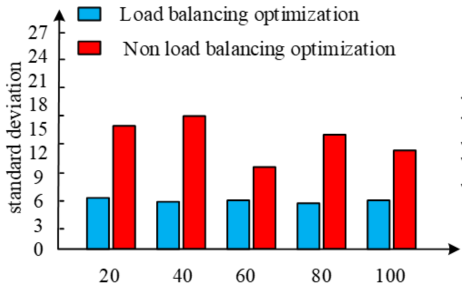
As shown in Fig. 4.2, when the maximum delay is 200ms and 250ms, the data storage overhead is optimized by 50%, 70%, 90% and 99% respectively. The experimental results show that the storage overhead of the system is gradually reduced in the process of continuous iteration of genetic algorithm. In the ninth generation, the method has basically reached a stable state, and the data storage overhead has been significantly reduced compared with that before optimization. Experimental results show that the method has good convergence performance and optimal degree. In particular, when the maximum delay is 200 milliseconds, the savings cost of the first generation is $65.234, of which only $14.631 at 50%, a decrease of 78%. At 70%, the optimal savings cost is only $20.896, which is 69.68% less than the original. At 90%, the optimal savings cost is only $33.199, which is 48.94% less than the original. In 99% of the cases, the optimal savings cost is only $50.398, which is 22.03% less than the original. Similarly, when the maximum delay is 250 milliseconds, the optimization at the proportion of 50% can save 81.01%. Under the proportion of 70%, the best savings cost was only 15.907 US dollars, a decrease of 76.44%. Under the proportion of 90%, the best savings cost is $25.023, which is reduced by 63.26%. In 99% of the cases, the best savings cost was only $35.407, a decrease of 47.21%. The results show that under the same number of users, when the maximum delay is long, the storage overhead of the system is small. The reason is that in order to meet the higher demand of social services, it is necessary to store replicas in more locations to ensure lower latency, which leads to the increase of overhead. The research results of this project will further verify the correctness and feasibility of this method. In summary, the social network data placement model aims to optimize the storage of social media data in a cloud computing environment to reduce data transmission costs and improve access efficiency. The model uses genetic algorithms to adaptively select data storage locations in different data centers, considering factors such as data access frequency, storage



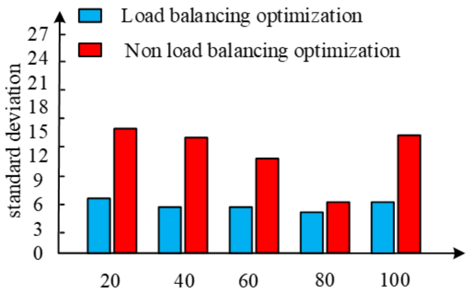
(a) 50% of users meet delay requirements



(b) 70% of users meet delay requirements

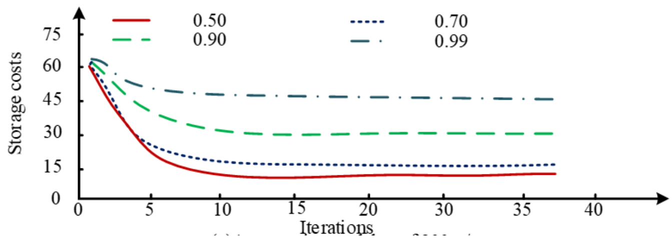


(c) 90% of users meet delay requirements

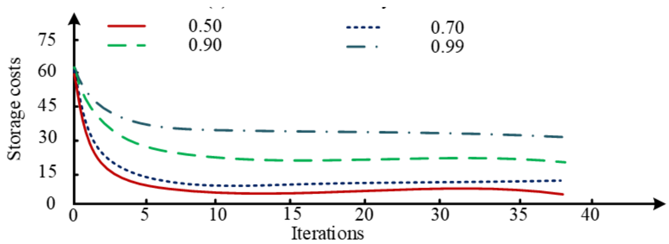


(d) 90% of users meet delay requirements

Fig. 4.1: Load comparison status



(a) At a maximal delay of 200 meter per second



(b) At a maximal delay of 250 meter per second

Fig. 4.2: The result of storage cost changing with the number of iterations load comparison status

Table 4.2: Dataset situation

Time	Total number of blog posts	Number of employees issuing documents	Average number of documents issued by employees	Standard error
Jan	85590	6783	12.62	16.98
Feb	103700	8381	12.37	17.12
Mar	102850	8762	11.74	16.52
APR	90920	7845	11.59	17.07
May	95100	7554	12.59	22.11
Jun	85290	6861	12.43	17.06
Jul	88850	7142	12.44	16.56
Aug	88880	7110	12.50	16.02
Sep	72820	5812	12.53	15.98
OCT	72610	5472	13.27	16.68
Nov	74120	5515	13.44	16.72
Dec	68100	5132	13.27	18.21

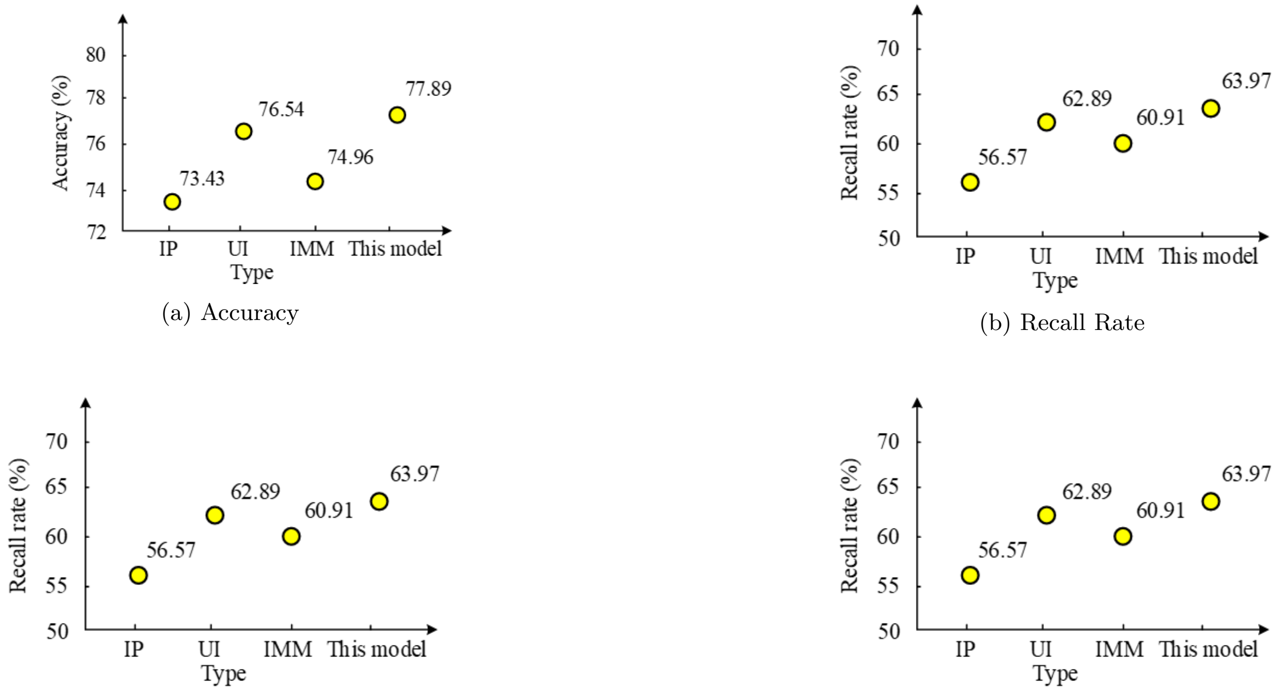
costs of data centers, and network latency. Through experimental tests, the model successfully reduces data transmission and storage costs while ensuring that the response time of user access remains within acceptable limits. This significantly improves the overall performance and resource utilization of the data center.

4.2. Social network interaction model test under human resource management of Multinational Enterprises.. To validate the performance effectiveness of the enterprise social network interaction model, the study used data on the total number of enterprise blog posts, the number of employees, and the average number of employee posts over a one-year period. The test metrics included accuracy, recall, F1 score, and precision. By comparing these metrics, the interactivity of the employee social interaction model can be further analyzed across different dimensions, including the relationship between employee rank and blog post, and blog post to blog post.The data set is shown in Table 4.2.

Supported by the data from the above data sets, the study conducted a comparative analysis on the accuracy, recall rate, F1 score and precision of the model. The results are shown in Fig. 4.3.

As shown in Fig. 4.3, the accuracy of the research model is the best, with an accuracy of 77.89%, while the accuracy of other models is below 76.54%. Secondly, in terms of recall rate, the research model is also superior to other models, reaching 63.97%. The recall rate of other models was below 62.89%. Looking at F1 score, the F1 score of the research model is 70.32%, which is higher than other models, which proves the superiority of the research model again. Finally, the precision of the research model is 71.78%, which is higher than that of other models, which shows that the research model is better in the accuracy of prediction results. In conclusion, the research model is superior to other models in accuracy, recall, F1 score and precision. This shows that the model has higher accuracy and robustness in the prediction and analysis of enterprise social network interaction, and can provide more reliable decision support for enterprises. The interaction analysis results are shown in Fig. 4.4.

As shown in Fig. 4.4, the analysis of the enterprise social network interaction model covers three dimensions: the interaction between employee rank and rank, the interaction between employee rank and blog category, and the interaction between blog category and blog category. The experimental results show that when forwarding a blog post, employees are affected by the rank of the author, especially when the author of the blog post is the direct leader of the employee, employees are more willing to forward the blog post. This phenomenon can be explained as waterfall effect or domino effect, that is, in the organization, the influence of direct leaders of subordinates can neutralize the influence of indirect leaders at higher levels, making it difficult for this influence to spread across levels. The analysis reveals a correlation between employee rank and the categories of blog posts they read and share. With the promotion of rank, employees tend to read and forward blog posts related to the working environment. For employees at higher and lower levels, they prefer to read and forward blog posts related to work content. For intermediate level employees, they are more willing to share content related



(a) Accuracy

(b) Recall Rate

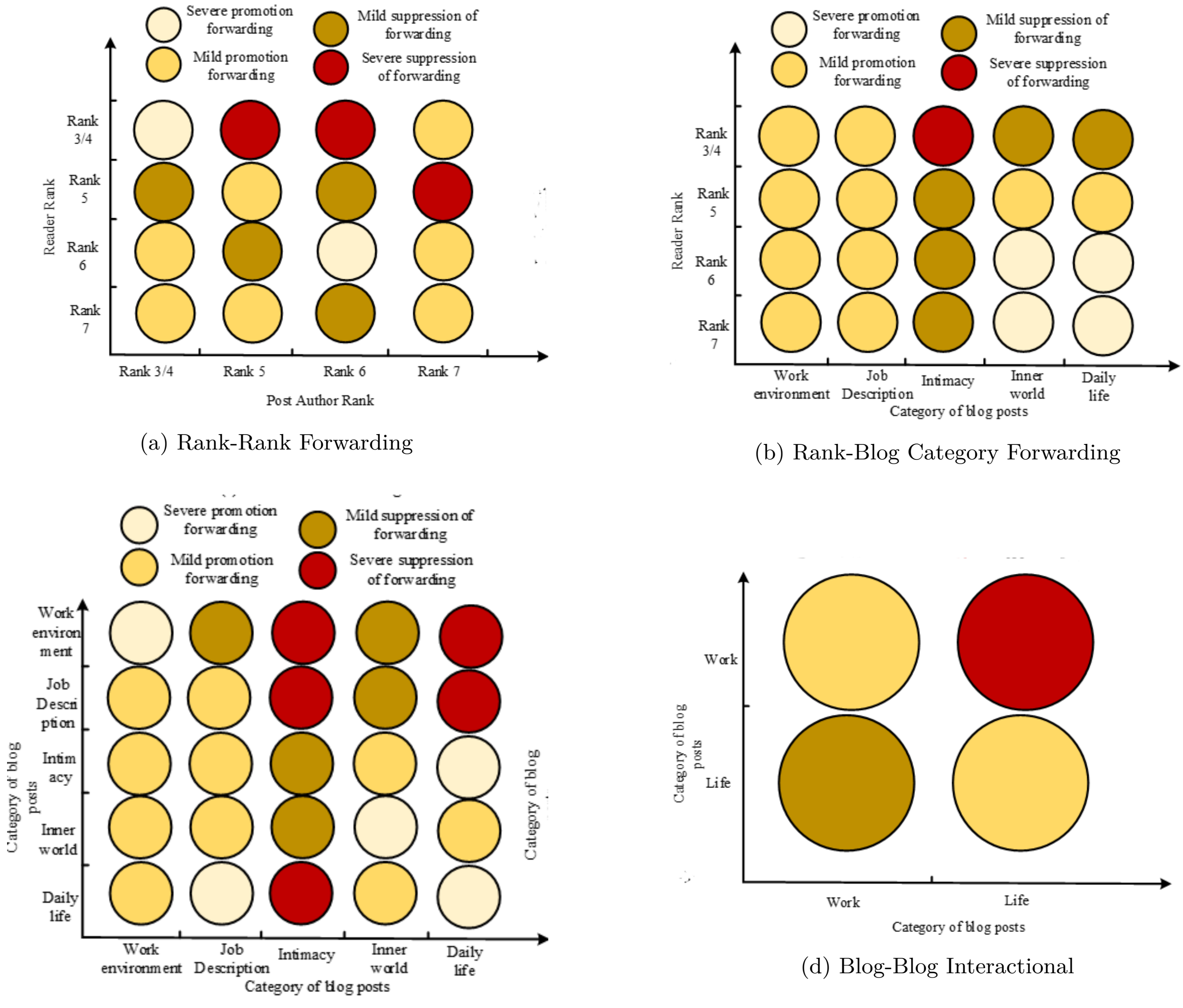
(c) Recall rate (%)

(d) Precision

Fig. 4.3: Performance index dataset situation

to intimacy. In the analysis of the interaction between blog categories and blog categories, it is found that there is a competitive relationship between different types of blog posts. Blog posts of intimate relationship have the strongest inhibitory effect on other types of blog posts. The study proposes a social network interaction model that can classify blog posts and infer interactions among employees through a co-training approach optimized by a genetic algorithm. The model accurately predicts employee interaction tendencies, such as which blog posts specific groups of employees are more likely to read, comment on, or share. This text provides insights into how employees connect and share knowledge in corporate social networks. Understanding these connections can help companies optimize their internal communication strategies and improve productivity.

5. Conclusion. This paper proposes an adaptive intelligent data placement strategy based on genetic algorithm, and realizes the load balancing of server resources by constructing a fitness model. At the same time, an effective interaction model of enterprise social network is designed to improve the interaction efficiency of enterprise social network. The results showed that when the maximum delay was 200 milliseconds and 250 milliseconds, the data storage overhead was optimized by 50%, 70%, 90% and 99% respectively, and the storage overhead of the system was gradually reduced. Especially when the maximum delay was 200 milliseconds, the savings cost of the first generation was \$65.234, which was only \$14.631 at 50%, a decrease of 78%. Similarly, when the maximum delay was 250 milliseconds, the optimization at the proportion of 50% can save 81.01%. In the test of enterprise social network interaction model, the research model is superior to other models in accuracy, recall rate, F1 score and precision. Specifically, the accuracy of the model was 77.89%, the recall rate was 63.97%, the F1 score was 70.32%, and the precision was 71.78%. This shows that the model has higher accuracy and robustness in the prediction and analysis of enterprise social network interaction. Although this study achieved significant results in data analysis, there are still limitations. For instance, the use of genetic algorithms as the basis of the model requires parameter adjustments to obtain optimal solutions. However, the



(a) Rank-Rank Forwarding

(b) Rank-Blog Category Forwarding

(c) Blog-Blog Interactional

(d) Blog-Blog Interactional

Fig. 4.4: Performance index dataset situation

stochastic nature of the algorithms may lead to fluctuations in the experimental results, which can affect model stability and reliability. Additionally, the dataset utilized in the study was limited to a specific company and did not account for other metrics related to flexibility and adaptability. This may restrict the generalizability of the model. To enhance the stability and reliability of the model, future research should consider more efficient algorithms, expand the dataset, and incorporate the effects of dynamic changes in social networks.

REFERENCES

[1] Cao, Y., Shao, Y. & Zhang, H. Study on early warning of E-commerce enterprise financial risk based on deep learning algorithm. *Electronic Commerce Research*. **22**, 21-36 (2022)
[2] Chen, M. The influence of big data analysis of intelligent manufacturing under machine learning on start-ups enterprise.

Enterprise Information Systems. **16**, 347-362 (2022)
[3] Nezhadkian, M., Azimi, S., Ferro, A. & Nafei, A. A Model for New Product Development in Business Companies Based on Grounded Theory Approach and Fuzzy Method. *Journal Of Computational And Cognitive Engineering*. **2**, 124-132 (2022)
[4] Liang, M., Xin, Z., Yan, D. & Jianxiang, F. How to improve employee satisfaction and efficiency through different enterprise social media use. *Journal Of Enterprise Information Management*. **34**, 922-947 (2021)
[5] Luqman, A., Talwar, S., Masood, A. & Dhir, A. Does enterprise social media use promote employee creativity and well-being?. *Journal Of Business Research*. **131** pp. 40-54 (2021)
[6] Yousaf, S., Rasheed, M., Kaur, P., Islam, N. & Dhir, A. The dark side of phubbing in the workplace: Investigating the role of intrinsic motivation and the use of enterprise social media (ESM) in a cross-cultural setting. *Journal Of Business Research*. **143** pp. 81-93 (2022)
[7] Cloud computing, S. an overview of big data challenges and opportunities for large enterprises. *International Research Journal Of Modernization In Engineering Technology And Science*. **4**, 1331-1337 (2022)
[8] Vinoth, S., Vemula, H., Haralayya, B., Mamgain, P., Hasan, M. & Naved, M. Application of cloud computing in banking and e-commerce and related security threats. *Materials Today: Proceedings*. **51** pp. 2172-2175 (2022)
[9] Namasudra, S. Data access control in the cloud computing environment for bioinformatics. *International Journal Of Applied Research In Bioinformatics (IJARB)*. **11**, 40-50 (2021)
[10] Li, Y., Shi, S., Wu, Y. & Chen, Y. A review of enterprise social media: visualization of landscape and evolution. *Internet Research*. **31**, 1203-1235 (2021)
[11] Liang, M., Xin, Z., Yan, D. & Jianxiang, F. How to improve employee satisfaction and efficiency through different enterprise social media use. *Journal Of Enterprise Information Management*. **34**, 922-947 (2021)
[12] Luqman, A., Talwar, S., Masood, A. & Dhir, A. Does enterprise social media use promote employee creativity and well-being?. *Journal Of Business Research*. **131** pp. 40-54 (2021)
[13] Laitinen, K. & And, S. and constraints on employees' information sharing on enterprise social media. *Information Technology & People*. **34**, 642-665 (2021)
[14] Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A. & Trichina, E. Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review. *The International Journal Of Human Resource Management*. **33**, 1237-1266 (2022)
[15] Ngoc Su, D. & Luc Tra, D. Thi Huynh H M, Hai Hong Thi Nguyen,Barry O'Mahony. *Enhancing Resilience In The Covid-*. **24**, 3189-3205 (2021)
[16] Guest, D., Sanders, K., Rodrigues, R. & Oliveira, T. Signalling theory as a framework for analysing human resource management processes and integrating human resource attribution theories: A conceptual analysis and empirical exploration. *Human Resource Management Journal*. **31**, 796-818 (2021)
[17] Vinoth, S., Vemula, H. & Haralayya, B. Pradeep Mamgain,Mohammed Faez Hasan, Mohd Naved. *Application Of Cloud Computing In Banking And E-commerce And Related Security Threats*. **51** pp. 2172-2175 (2022)
[18] Sandhu, A. Big data with cloud computing: Discussions and challenges. *Big Data Mining And Analytics*. **5**, 32-40 (2021)

Edited by: Zhengyi Chai
Special issue on: Data-Driven Optimization Algorithms for Sustainable and Smart City
Received: Nov 8, 2023
Accepted: Mar 4, 2024