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Deep Neural Network-based Optimal Path Selection for Propagation Information and Its Enhancement on Data Flow Efficiency

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ABSTRACT
The rapid development of the information age has prompted the exchange and sharing of information resources more and more frequently. Aiming at the problem of propagating information data in the center of data network, which is easy to cause congestion and delay, this paper uses deep neural network to research on the optimal path selection method for propagating information. A network traffic prediction model is designed based on multi-task learning and LSTM, and a dynamic multipath load balancing algorithm (FNN-LB) based on feed-forward neural network is proposed to solve the problem of scheduling and allocation of network traffic. The traffic prediction accuracy and generalization ability of the MT-LSTM model are verified, and the prediction mean square error is only 0.573%. Analyzed from several performance metrics, the FNN-LB algorithm improves the network throughput by 2.34% to 10.35% relative to other algorithms, effectively reduces the number of idle and overloaded links, as well as the average network delay and packet loss rate of the rat flow, while the first packet round-trip delay of the rat flow is reduced by more than 12.58%. Therefore, the proposed method in this paper can ensure the transmission quality of communication information data and improve the efficiency of data flow of communication information.

Keywords: deep neural network; multi-task learning; LSTM; feed-forward neural network; optimal path selection

1. Introduction

Media convergence refers to the development trend of traditional media turning to network emerging media to deeply integrate at the level of technology, content, channels and other levels based on Internet technology, as well as the emergence of emerging technologies such as 5G, big data,

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cloud computing, artificial intelligence, and so on, which in turn forms a new media ecological pattern [1-2]. From the technical level, media convergence is reflected in the integrated operation of the communication platform, intelligent processing of information distribution and personalized presentation of user experience [3]. From the content level, it is manifested in the deep integration of multimedia forms, the collaborative innovation of content production and the upgrading and reshaping of communication value [4]. From the channel level, it is the integration of multi-platform resources, the layout of all-media matrix and the three-dimensionalization of communication channels [5]. Information dissemination effectiveness, as an important indicator of the quality and efficiency of the communication system, is affected by multiple factors such as the communication subject, communication channels, audience feedback, etc. Invoking the theory of communication, it emphasizes the accuracy, timeliness and effectiveness of the information transmission under specific time and space conditions [6-8].

The global wave of digital intellectualization has been iteratively upgraded, and the traditional media have accelerated their evolution to modern new mainstream media. This not only changes the technical path and organization of information dissemination, but also profoundly affects the communication effect and social value realization [9-10]. With the advent of the era of network media convergence, traditional media are facing unprecedented impact and change, and the way, speed and breadth of information transmission have undergone a radical change. The new era has had a great impact on traditional media, and even redefined to some extent how people view, receive and disseminate information [11-13]. In this context, the concept of "information dissemination effectiveness" needs to be re-examined and redefined. Information dissemination effectiveness is not only a measure of whether a message is successfully communicated, but also concerns the authenticity and effectiveness of the message as well as its actual impact on the audience [14-15]. Under the background of network media convergence, information dissemination is characterized by technological empowerment, scene diversification, and interactive deepening, which not only creates new opportunities for enhancing communication effectiveness, but also brings new challenges such as information overload, communication distortion, and discourse misbehavior [16-18]. Based on this, in-depth study of the influence mechanism and optimization path of information dissemination effectiveness in the context of media integration is not only a theoretical issue, but also an urgent task for mainstream media to grasp the law of dissemination and adhere to the position of public opinion in news practice.

Research on information dissemination mainly contains the exploration of factors affecting information dissemination, and the optimization path of information dissemination. Studies focusing on factors affecting information dissemination include, literature [19] empirical study based on the refined likelihood model reveals that elements on both the central and peripheral paths of ELM positively promote the dissemination of individual information. Literature [20] used an econometric model to explore the factors influencing the dissemination of public opinion, and found that in addition to the information content and information sources, the information channel is also a greater concern, and the more the total amount of information disseminated to users, the more it reduces the dissemination of public opinion information. Literature [21] talks about the role played by opinion leaders in the dissemination of information on the Internet, which can disseminate the largest number of objects in the shortest time, and the process of information dissemination is efficient and effective. Literature [22] used the two-stage model of Feedback-Sympathy-Identification-Participant-Sharing (FSIPS) to analyze the process and characteristics of information dissemination, and pointed out that the rate of liking has a significant impact on the effect of information dissemination.

While focusing on the research of information dissemination optimization as follows, literature [23] conceived a strategy of integer linear programming and multi-criteria optimization of information dissemination problems, which can assist institutions to make scientific decisions on information dissemination and management. Literature [24] systematically summarizes the information dissemination research models and literature, and looks forward to the future development trend of information dissemination models, which provides a reference for researchers in the field of information dissemination. Literature [25] introduces Telematics applications and tries to implant real-time content dissemination scheme in Telematics architecture to reduce the response time of traffic management services. Literature [26] combines the online social network information dissemination model built based on user and information attributes to investigate the current status of information dissemination of different network architectures in each law, which confirms the effectiveness and feasibility of the proposed model.

The study first utilizes LSTM neural network and multi-task learning to establish a prediction model for propagating information data flow. Subsequently, the detection and labeling of elephant flow is deployed to the host side, the network topology information is constructed through the LLDP protocol, and the OpenFlow protocol is utilized to obtain the flow information of each link segment, so as to conduct real-time monitoring of the underlying network conditions. Then feed-forward neural network is used to predict the link load value, which is associated with the heuristic information in the heuristic ant colony algorithm, so that the path deployment of the final elephant flow is dynamically adjusted based on the real-time link status, thus realizing the optimal selection of paths for the propagation of information. Based on this, experimental simulations are conducted to compare the traffic prediction accuracy of LSTM and the MT-LSTM model. The FNN-LB algorithm of this paper is analyzed with ECMP, Hedera, and Q-Learning algorithms in terms of average throughput, link utilization, link bandwidth utilization, first-packet loss rate and round-trip delay of the mouse flow, and the average round-trip delay and packet loss rate of the mouse flow, to explore the effect of this paper's method on the improvement of the efficiency of the data flow of the propagation information.

2. Deep neural network-based optimization path for disseminating information

In the information age, massive information resources enrich people's cultural life, but also put forward new requirements for the management and maintenance of network resources. Combining deep neural network algorithms on the basis of software-defined network (SDN) architecture and enhancing the self-learning habit of routing strategies are of great significance and application prospects for optimizing the scheduling of propagation information traffic in data center networks. In this paper, based on deep neural networks, we design traffic prediction and optimized path selection methods for network propagation information.

2.1. MT-LSTM based traffic prediction

2.1.1. LSTM neural networks. By processing and learning from the traffic information, we can predict the flow proportion of the traffic at the next moment, thus guiding the bandwidth scheduling problem of the data center.LSTM can not only learn the long distance traffic features but also selectively forget some traffic features by optimizing the model structure, which is conducive to the deeper prediction of the traffic in the time dimension. The LSTM contains three “gate” structures whose main function is to filter the information in the network model during the message iteration process. The “gate” structures in the model are essentially Sigmoid activation functions and bitwise multiplication operations applied to the state information.

Oblivion gates and input gates help the entire network to have a more efficient long term memory, and these two “gates” are the core of the entire recurrent network model. The forgetting gate filters out useless information based on the input x_t of the current round and the output h_{t-1} of the previous round.

If state c is a n-dimensional vector, then x_t and h_{t-1} can be substituted into Eq. (1), and Eq. (1) can be processed by the sigmoid activation function to output a n-dimensional vector f, and by the nature of the sigmoid activation function, the values of f are all in the range of 0 to 1:

$$f = Sigmoid\left(W_l x + W_2 h\right) \tag{1}$$

After that, the state c_{t-1} of the previous round will do a bitwise multiplication operation with the output f. At this time, if the information close to 0 in f will be weakened continuously, and the information close to 1 will be preserved.

The LSTM network structure will continuously filter the previous state information, and then the "input gate" can be used to extract valid information from the input of the current round, and the "input gate" will determine, according to the input x_t of this round and the output h_{t-1} of the previous round, so as to output a new state c together with c_t. It can be seen that the retention of information in the network structure can be well controlled by the "forgetting gate" and "input gate".

After the calculation of the "forgetting gate" and the "input gate", the LSTM will determine the output of this round according to the new state of the output, and the information needed at this time is state c_t, h_{t-1} and x_t, so as to confirm the output h_t at the current moment. From the above description, it can be seen that the forward propagation logic of LSTM is relatively complex, and the specific operation process of each gate is as follows:

$$z = \tanh\left(W_z\left[h_{t-1}, x_t\right]\right) \tag{2}$$

$$i = Sigmoid\left(W_i\left[h_{t-1}, | \, x_t\right]\right) \tag{3}$$

$$f = Sigmoid\left(W_f\left[h_{t-1}, x_t\right]\right) \tag{4}$$

$$o = Sigmoid\left(W_o\left[h_{t-1}, x_t\right]\right) \tag{5}$$

$$c_t = f \cdot c_{t-1} + i \cdot z \tag{6}$$

$$h_t = o \cdot \tanh c_t \tag{7}$$

W_z, W_i, W_f, and W_o in the above equation are model parameters of dimension $[2n, n]$.

2.1.2. Multi-task learning. Multi-task learning (MTL) machine learning methods aim to improve the overall model performance by learning and optimizing multiple related tasks simultaneously. Compared with traditional single-task learning, multitask learning can share the ability to exploit the commonalities and correlations between different tasks, thus improving the learning efficiency and generalization ability. The key idea of multitask learning is to promote interdependence and complementarity by jointly learning multiple tasks. A shared model or feature representation can capture common patterns and knowledge across different tasks, thereby improving model representation and generalization performance.

2.2. Optimized path selection based on FNN-LB

2.2.1. Model Architecture. The architecture of the dynamic multipath load balancing mechanism based on feed-forward neural network (FNN-LB) proposed in this chapter is shown in Fig. 1. First, the elephant stream is discovered and labeled by the stream detection program in the host terminal according to the data size of the transmitted bytes in the data stream. The topology-aware module obtains the global view of the network according to the Link Layer Discovery Protocol (LLDP).The FNN-LB mechanism is a load balancing mechanism based on multiple network states, so in the flow information monitoring module, the information interaction between the control layer and the data layer is realized through the OpenFlow protocol, so as to carry out the real-time monitoring of the underlying network conditions, and to obtain the bandwidth utilization rate, delay, packet loss rate, and other flow information of each link segment. The OpenFlow protocol realizes the interaction between the control layer and data layer information, so as to monitor the underlying network condition in real time, and obtain the bandwidth utilization, delay, packet loss rate and other traffic information of each link. The feed-forward neural network module takes these underlying network characteristics as inputs and predicts the corresponding load of each link segment. Finally, the routing module uses the optimized ant colony algorithm to make the optimal path converge to the link with a low estimated load value, which ensures the demand of high throughput during the transmission of elephant streams and realizes the dynamic load balancing of paths.

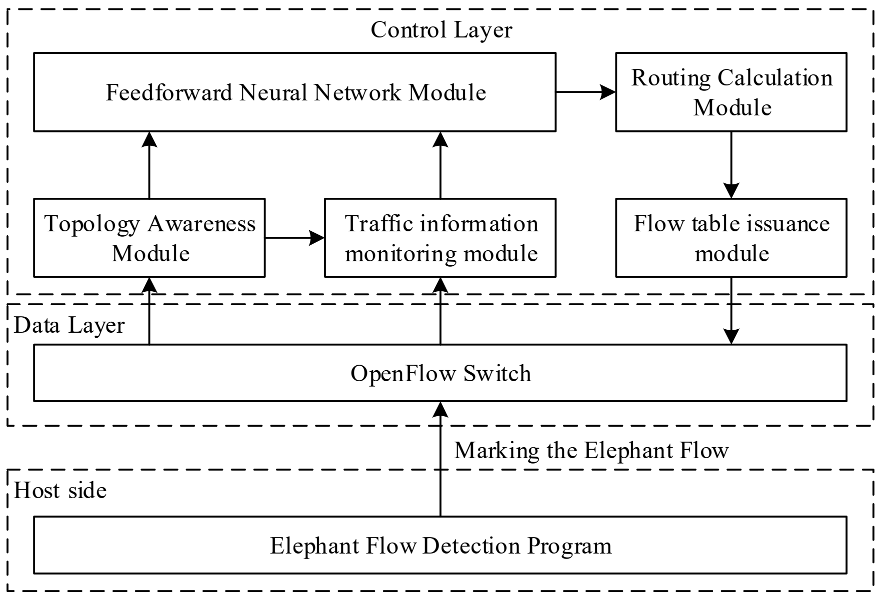


Fig. 1. The architecture of FNN-LB

2.2.2. Network Topology Awareness. In order to reduce the consumption of network resources, the Packet_out message is changed from one per port to one per switch. When a switch receives an LLDP packet from a controller port, it modifies its source MAC address to the port MAC address and then forwards it from the corresponding port. When the next switch receives an LLDP packet from a non-controller port, it encapsulates it again into a Packet_in message and uploads it to the controller. By parsing the packet, the controller then obtains information about the destination switch, destination port, source MAC address, and source switch, and obtains the logical connectivity of the link from their correspondences.

2.2.3. Traffic information monitoring module. Adopting the periodic monitoring mechanism, according to the OpenFlow protocol, the controller can predefine the period T and send statistical request messages to all the switches connected to it to obtain information about ports, flow tables, flow table entries and group tables.

1) Bandwidth utilization:

$$BW_{ratio}^{uv} = \frac{B_T^{uv} - B_{T-1}^{uv}}{BW_{\max}^{uv}} \tag{8}$$

where B_T^{uv} and B_{T-1}^{uv} are the total number of bytes sent by the link between switches u and v, respectively, in two adjacent time periods. $BW_{\max}^{uv}$ is the maximum bandwidth of link (u, v).

2) Time delay: By parsing the LLDP packets in the link discovery protocol and the Echo packets in the control message protocol, the sending and receiving timestamps of the two are obtained, from which the forward and reverse transmission delay of the two is obtained. The average transmission delay of the link segment:

$$T_{dealy}^{uv} = \frac{1}{2}\left[\left(t_{lldp}^{uv} + t_{lldp}^{vu}\right) - \left(t_{echo}^{uv} + t_{echo}^{vu}\right)\right] \tag{9}$$

Where t_{lldp}^{uv} is the forward delay of the LLDP packet from the controller down to switch u, then from switch u to switch v, and finally back to the controller. t_{lldp}^{vu} is the reverse delay of the LLDP packet sent from the controller first to switch v, then to switch u, and finally back to the controller. Similarly, t_{echo}^{uv} and t_{echo}^{vu} are the forward and reverse delays for Echo packets, respectively. T_{dealy}^{uv} is the average transmission delay between switch u and switch v.

3) Packet loss rate:

$$P_{loss} = \frac{P_{tx}^{uv} - P_{rx}^{uv}}{P_{tx}^{uv}} \tag{10}$$

where P_{tx}^{uv} and P_{rx}^{uv} are the number of packets sent and the number of packets received between links (u,v), respectively.

2.2.4. Feedforward Neural Network Module. A three-layer feed-forward neural network structure is used. The input-output relationship of the hidden layer neurons can be represented by Eq. (11) and Eq. (12), and the link load of the final output can be represented by Eq. (13):

$$a_o = \sum_{i=1}^{n} w_{oi} x_i + \theta_o \left(i = 1,2,\ldots,n; o = 1,2,\ldots,h\right) \tag{11}$$

$$z_o = f\left(a_o\right)\left(o = 1,2,\ldots,h\right) \tag{12}$$

$$Load = f\left(\sum_{j=1}^{h} w_j z_o + \theta\right)\left(j,o = 1,2,\ldots,h\right) \tag{13}$$

Where, x_i is the input value of the input layer. w_{oi} is the connection weight between the neurons of the input layer and the hidden layer. w_j is the connection weight between the hidden and output layer neurons. θ_o and θ are the thresholds of the hidden and output layer neurons, respectively. $f(x)$ is the activation function, a_o and z_o are the input and output values of the hidden layer respectively. Load is the link load.

2.2.5. Routing module. In this module, the controller needs to determine whether the stream to be processed is an elephant stream or a mouse stream. The scheduling of the elephant flow uses the optimized ant colony algorithm for path computation. The specific steps are as follows:

1) Perform initialization settings. One is to set the main parameters involved in the ACO algorithm. The second is network information acquisition for determining the number of optimal paths required.

2) Determine the current position and calculate the transfer probability. After the ants are located at the start node, the transfer probability can be calculated according to Eq. (14):

$$P_{uv}^{k}(t) = \begin{cases} \dfrac{\left[\tau_{uv}(t)\right]^{\alpha} \cdot \left[\eta_{uv}(t)\right]^{\beta}}{\sum\limits_{s \in albwed} \left[\tau_{us}(t)\right]^{\alpha} \cdot \left[\eta_{us}(t)\right]^{\beta}}, & v \in allowed_k \\ 0, & v \notin allowed_k \end{cases} \tag{14}$$

where $P_{uv}^k(t)$ denotes the probability of ant k moving from switch u to switch v at the t moment. τ_{uv} is the pheromone strength between links l_{uv}. η_{uv} denotes the heuristic information of link l_{up}. α and β are the weighting factors of pheromone and heuristic information respectively. $allowed_k$ is the set of all switches that are optional for the next hop when ant k is at switch u. The $allowed_k$ set will be updated when the ant selects and moves to the next hop node.

3) Combine the roulette wheel selection algorithm (RWS) to select the next hop node. If ant k is at switch u when the next hop has a total of m switches to choose. First, the transfer probability of these m switches can be calculated from Eq. (14), and then the cumulative probability of these switches can be calculated according to Eq. (15). Then, a random number r is generated in the interval $[0,1]$. If $0 \le r \le q_1$, switch 1 is selected as the next hop node. If $q_{d-1} < r \le q_d (2 \le d \le m)$, then switch d is selected as the next hop node:

$$q_v = \sum_{i=1}^{v} P_{ui}^k \tag{15}$$

4) Determine whether the ant has reached the destination node. If the ants have not reached the destination node then go back to step (2) and continue to find the next hop node. If the destination node has been reached, turn to step (5) and make the number of arriving ants plus 1.

5) Judge whether all the ants in the colony have reached the destination node according to the number of arriving ants. If yes, turn to step (6) and make the number of iterations plus 1. If no, turn back to step (2) and operate on the next ant.

6) Update the pheromone concentration on the path:

$$\tau_{uv}(t+1) = (1-\rho)\cdot\tau_{uv}(t) + \sum_{k=1}^{N} \Delta\tau_{uv}^k(t) \tag{16}$$

$$\Delta\tau_{uv}^k(t) = \begin{cases} \dfrac{Q}{hop_k}, & (u,v) \in path_k \\ 0, & otherswise \end{cases} \tag{17}$$

where $0 < \rho \le 1$ is the evaporation rate of the pheromone, and $1-\rho$ represents the residual factor of the pheromone after volatilization. Q is the total amount of pheromone. N is the number of ants. $path_k$ denotes the path passed by ant k. hop_k is the number of hops of path $path_k$, which can be interpreted as the length of the path.

7) Determine whether the algorithm reaches the maximum number of iterations. If yes, stop the iteration and get all the alternative paths. If not, return to step (2) to continue iteration.

8) Select multiple deployment paths from the alternative paths according to the bandwidth requirement of the elephant flow.

3. Effectiveness of MT-LSTM for traffic prediction

3.1. *Experimental data*

In this section, multiple datasets of propagated information traffic records divided by 30 milliseconds are fed into the neural network, which is expected to obtain the inter-ToR, inter-cluster, and intra-cluster traffic ratios of 2560 servers for the next 15 milliseconds in the data format of a 2560 × 3 traffic ratio matrix. Data preprocessing is performed through three steps: data cleaning, data integration and data transformation.

3.2. *Experimental Procedures*

In the data preprocessing phase of the experiment, the data set is assembled into a 30 ms data set, which is reprocessed using the generate-tensor function, which converts the original dataframe format of the total traffic information of each server for 30 ms into the ratio of the traffic going to each server for 30 ms, and a tensor in the format of 6*2560 as a result is returned as an input to the LSTM model. Then, the next 15ms of total traffic information is converted to one tensor in 3*2560 format in the same way as a label for the model.

Next, the LSTM neural network is initialized, three fully connected layers are defined in the model, the output of the original algorithm is used to get the output of three variables using the three fully connected layers, and then the three outputs are spliced together to get the final prediction, and the prediction is subtracted from the labels, where a loss is computed for all the three and the three losses are scaled by the ratio of 0.4, 0.4 and 0.2 to be This ratio is due to the strong correlation between the three features of inter-ToR, inter-cluster, and intra-cluster traffic going ratio, and the third traffic ratio can be fully determined from the first two traffic ratios. The total loss of the model is obtained by this linear summation, which is fed into the backpropagation process until the model finally converges.

In order to verify the convergence efficiency of the LSTM (MT-LSTM) model based on multi-task learning, this paper compares it with the traditional LSTM model, and the variation curves of the training loss function of the two algorithms are shown in Figure 2, the loss function of the MT-LSTM is reduced to 0.0002 when the epoch is 40, while the LSTM is still 0.1521, indicating that the convergence speed of the MT-LSTM model is faster.

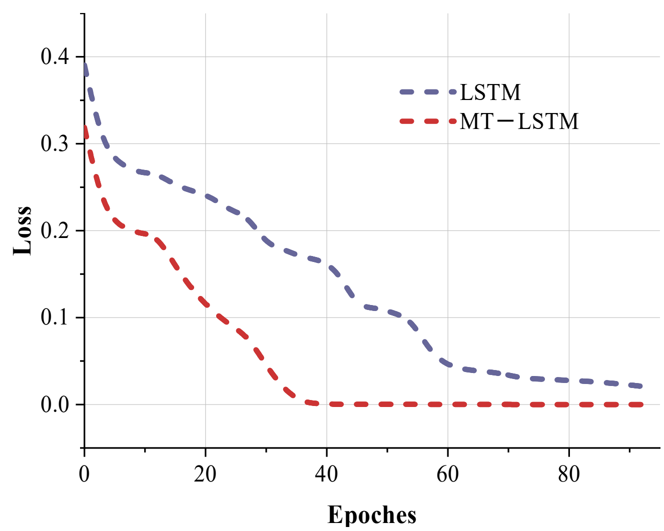
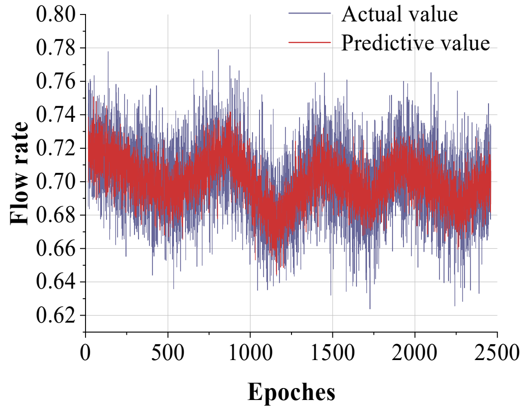


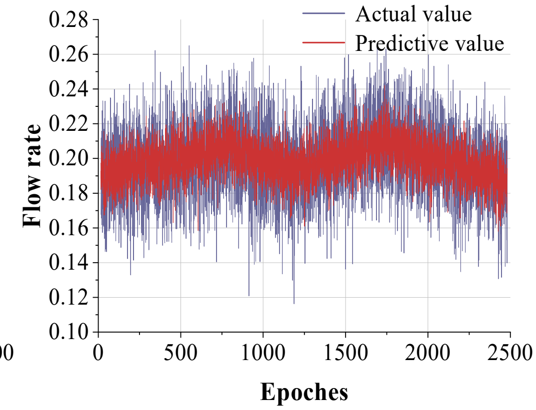
Fig. 2. Two kinds of algorithm training loss function change curve

3.3. *Projected results*

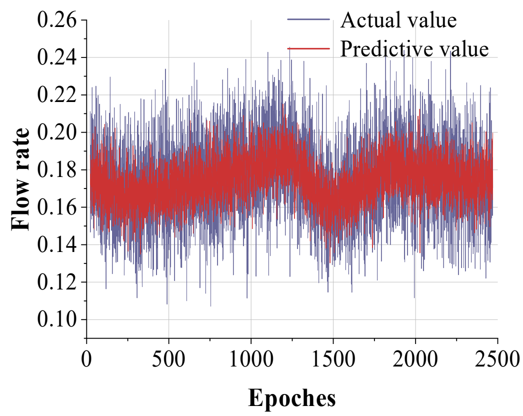
The prediction results and actual values of MT-LSTM for the three tasks are shown in Fig. 3, Figs. (a) (b) (c) correspond to the comparison of the predicted and actual values for each of the three tasks, with the predicted values in red and the actual values in purple in the following figure. The overall fluctuations of the predicted values are all slightly smaller than the actual values, and at the same time, due to the high burstiness of the information dissemination traffic in the data center, some of the bursty data streams cannot be accurately predicted by using the trained model. At the same time, due to the large amount of data, the two models are compared using the three metrics of MAE (Mean Absolute Error), MSE (Mean Squared Error) and RMSE (Root Mean Squared Error), and the error values of the two models are shown in Table 1.

The three error values of the MT-LSTM model are all less than those of the LSTM model. From a practical perspective, in predicting the future 15ms transmission information data center traffic direction, the mean squared error of the three traffic direction ratios for each server predicted using MT-LSTM is only 0.573%, which is a reduction of 2.682% compared to the RMSE of the LSTM algorithm. The LSTM algorithm based on multi-task learning used in this paper has higher accuracy in predicting information dissemination traffic at finer granularity, and its smaller error will not affect the accuracy of the optimized path selection strategy for disseminating information as well as affect the overall network performance.





(a)inter-ToR flow rate (b)inter-cluster flow rate



(c)intra-cluster flow rate

Fig. 3. MT-LSTM's prediction results and actual values for three tasks

Table 1. Error value of two models

	MT-LSTM	LSTM
MSE	0.573%	0.933%
RMSE	6.182%	8.864%
MAE	4.265%	5.925%

4. Effectiveness of data flow efficiency gains

In order to verify the effectiveness of the proposed deep learning network-based propagation information optimization path selection strategy in this paper, this section will build an experimental simulation environment to simulate the data center network topology and traffic to experimentally verify the proposed propagation information optimization path selection strategy, and compare and analyze the experimental results with ECMP, Hedera, and Q-Learning algorithms through different network performance metrics.

4.1. Simulation environment and settings

In order to verify the FNN-LB propagation information optimization selection strategy in SDN environment, this paper adopts Mininet+Ryu simulation platform to build the simulation environment. The Fat-Tree network topology of $K = 4$ elements built on Mininet is used for experimental simulation. 20 switches and 16 terminal hosts are included in the Fat-Tree network topology, in which the switches adopt OpenvSwitch switches supporting OpenFlow1.3, and the bandwidths of the links in the network are all set to 10 Mbit/s.

In order to verify the effectiveness of the FNN-LB propagation information optimization selection strategy, it is necessary to inject the propagation information traffic in the network environment, and make a judgment through the network performance. According to the characteristics of the propagation information network traffic, it is categorized into elephant flow and mouse flow in terms of traffic size, and "east-west" flow and "north-south" flow in terms of distribution. Combined with the traffic scheduling algorithm designed in this paper for the intra-Pod (Pod) and inter-Pod (Pod) methods are different, so that the simulation experiments in this paper simulate a total of four traffic models for the network environment, the four traffic models have different percentages of intra-Pod and inter-Pod traffic as shown below:

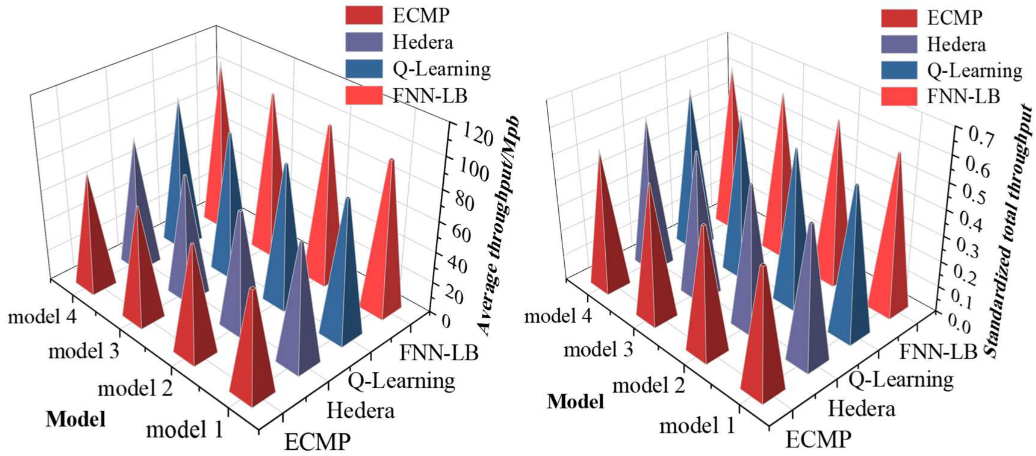
1) model 1: 25% of the traffic within the same Pod and 75% of the inter-Pod traffic.
2) model 2: 45% of the traffic within the same Pod and 55% of the inter-Pod traffic.
3) model 3: 55% of the traffic within the same Pod and 45% of the inter-Pod traffic.
4) model 4: 75% of the traffic within the same Pod and 25% of the inter-Pod traffic.

4.2. Performance indicators

The research objective of this paper is to safeguard the network transmission by intelligent scheduling of elephant streams in the network dissemination of information. Elephant flow is the main cause of network congestion and queuing delay increase, rat flow because of its small size and short duration, it has less impact on network performance, when the transmission of elephant flow is guaranteed, it will make the whole network performance are improved. In order to verify the effectiveness of the FNN-LB propagation information optimization selection algorithm proposed in this paper, the network performance is compared with the now commonly used ECMP, Hedera and Q-Learning algorithms by using the same flow model for a continuous experimental period of 60s under the Fat-Tree topology of $K = 4$ elements. The network performance metrics compared in this paper mainly include the average throughput of the network, link utilization, link bandwidth utilization, first packet loss rate and round-trip delay of the mouse flow, and the average round-trip delay and packet loss rate of the mouse flow.

4.3. Experimental results

4.3.1. Average throughput. The average throughput and normalized total throughput of the network are shown in Fig. 4. The FNN-LB optimized path selection strategy achieves the highest average throughput and normalized total throughput in all four models simulated.The relative performance improvement in total throughput of FNN-LB is shown in Table 2. The average network throughput and total throughput of FNN-LB are improved compared to ECMP, Hedera and Q-Learning, where the relative improvement over ECMP is 10.35%, over Hedera is 7.03% and over Q-Learning is 2.34%. This is strong evidence of the feasibility and effectiveness of FNN-LB.



(a)Average throughput (b)Standardized total throughput

Fig. 4. Average throughput and standardized total throughput of Internet

Table 2. Total throughput relativity improves of FNN-LB

Traffic scheduling strategy	ECMP	Hedera	Q-Learning	FNN-LB
Total throughput(Mbit)	828.03	853.73	892.85	913.71
Relative ascension	10.35%	7.03%	2.34%	0.00%

4.3.2. Link utilization. The network link utilization is shown in Fig. 5, and the relative performance improvement of network link utilization for FNN-LB is shown in Table 3. In general, the number of links being utilized in the network is higher when the percentage of intra-Pod traffic is low, while the number of links being utilized is lower when the percentage of intra-Pod traffic is high. Although FNN-LB achieves the highest network throughput among the four, its network link utilization is only 13.29% relatively higher than ECMP, while it is 3.45% relatively lower than Hedera and 1.51% relatively lower than Q-Learning.

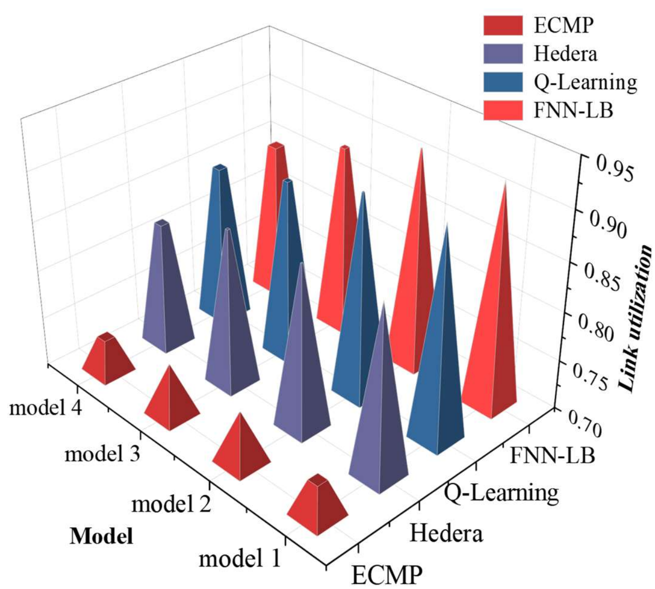


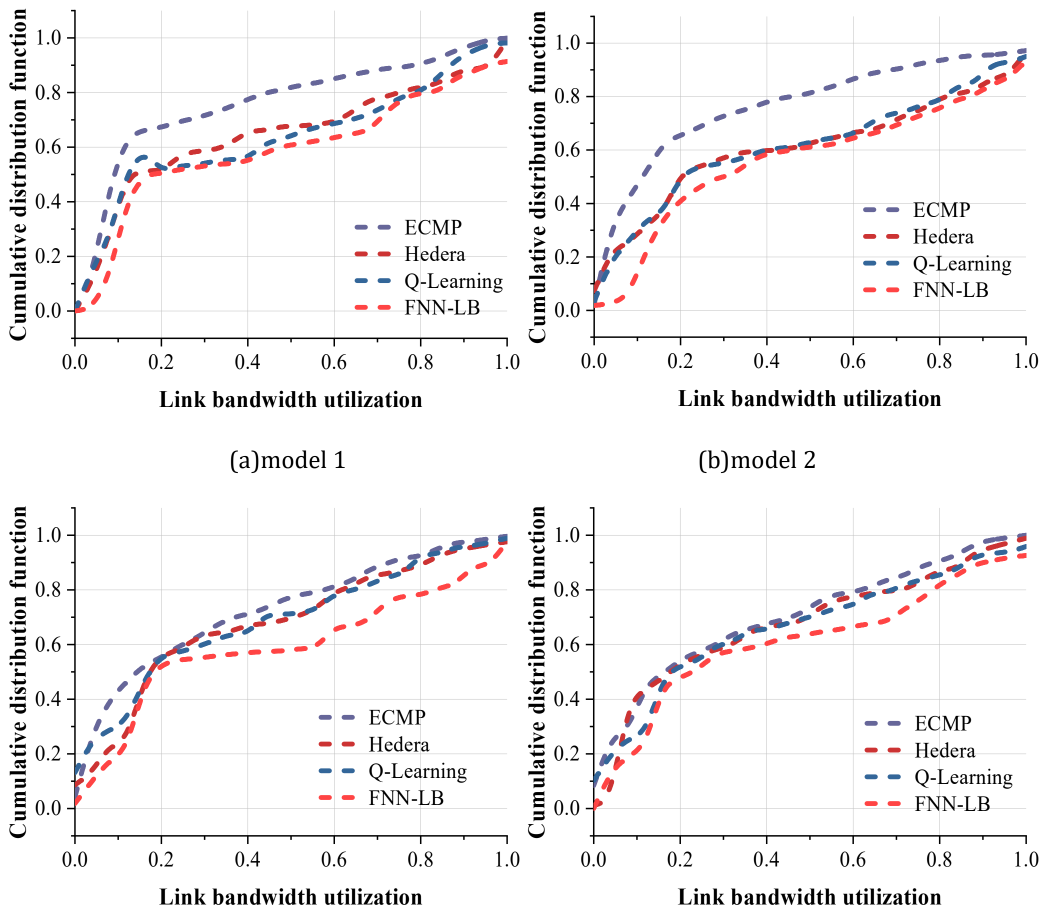
Fig. 5. Utilization of network link

Table 3. The increase of the relative power of the network link utilization of FNN-LB

Traffic scheduling strategy	ECMP	Hedera	Q-Learning	FNN-LB
The total number of links used	346	406	398	392
Relative ascension	13.29%	-3.45%	-1.51%	0.00%

4.3.3. Link Bandwidth Utilization. The bandwidth utilization of the network links is shown in Fig. 6, and the relative performance improvement of bandwidth utilization of FNN-LB is shown in Table 4. In general, the utilization of link bandwidth by ECMP, Hedera, Q-Learning, and FNN-LB varies greatly in the case of a lower percentage of traffic within the Pod. When the percentage of intra-Pod traffic is high, the utilization of link bandwidth by the four is closer.

Compared with ECMP, the number of links with bandwidth utilization less than or equal to 10% in Hedera, Q-Learning, and FNN-LB decreases significantly, indicating that the network resources are more fully utilized.The number of links with bandwidth utilization less than or equal to 10% in FNN-LB decreases by a relative amount of 7.79% compared to ECMP, 1.64% compared to Hedera, and 1.64% compared to Q-Learning. 1.64%, and 1.73% relatively less than Q-Learning, indicating that FNN-LB utilizes the network resources most fully, proving the feasibility and effectiveness of FNN-LB.



(a)model 1 (b)model 2

(c)model 3 (d)model 4

Fig. 6. Bandwidth utilization of network links

Table 4. The relativity of bandwidth utilization increases of FNN-LB

Traffic scheduling strategy	ECMP	Hedera	Q-Learning	FNN-LB
Bandwidth utilization⩽10% link ratio	55.98%	52.48%	52.53%	51.62%
Relative reduction	7.79%	1.64%	1.73%	0.00%

4.3.4. First Packet Loss Rate and Round Trip Delay. The performance metrics of first packet loss rate and round-trip delay are reflected by the performance of the rat flow, because rat flows in data center networks are generally delay-sensitive traffic. The first packet loss rate and round-trip delay of the mouse flow are shown in Figure 7 and Figure 8. The correlation between the first packet loss rate of the rat flow and the percentage of inter-Pod traffic in the traffic model is small and does not show a certain pattern. Under the four traffic models, the first packet loss rate of the mouse flow based on FNN-LB's propagation information optimization path selection method is 0, which achieves zero-loss transmission. The Q-Learning algorithm also achieves zero-loss transmission in traffic models model 1 and model 4, and the first packet loss rate is less than that of the model 2 and model 3, although it does not achieve zero-loss transmission. ECMP and Hedera algorithms.

The first-packet round-trip delay of the FNN-LB-based propagation information optimization path selection method for the rat flow is smaller than that of the ECMP, Hedera and Q-Learning algorithms, with an overall average reduction of 51.09%, 52.87% and 12.58%, respectively. The experimental results prove that the FNN-LB-based propagation information optimization path selection method can effectively guarantee the first-packet transmission of the rat flow in information propagation.

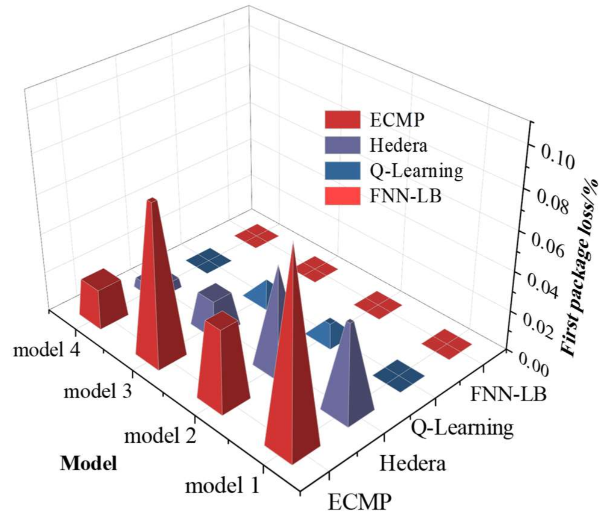


Fig. 7. Loss rate of mice flow first package

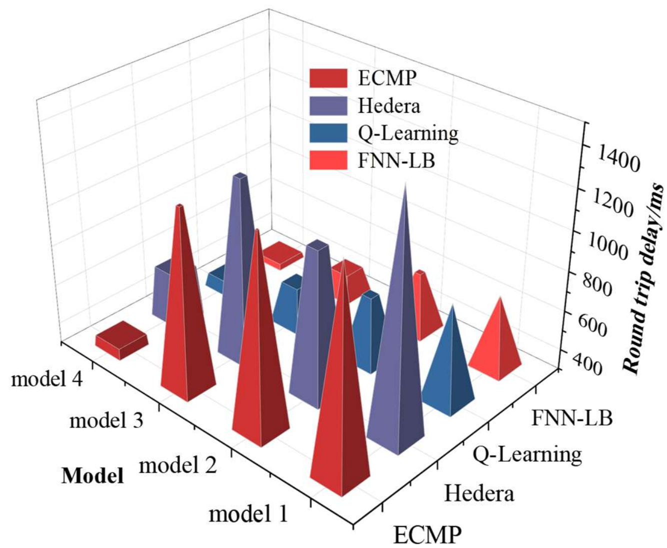


Fig. 8. Round trip delay of mice flow first package

4.3.5. Average round-trip delay and packet loss rate:

1) Average round-trip delay of rat flow. The problem of transmission delay in network information dissemination is analyzed by the average round-trip delay of the rat flow. The average round-trip delay of the mouse flow is shown in Fig. 9. The average round-trip delay of the FNN-LB-based optimal path selection method for propagating information is smaller than that of ECMP, Hedera and Q-Learning algorithms in different traffic models. Among them, the FNN-LB algorithm reduces 4.97% to 67.75% in traffic model model 1, 25.34% to 65.17% in model 2, 3.08% to 66.08% in model 3, and 1.56% to 20.92% in model 4. The optimized path selection algorithm for propagation information based on FNN-LB effectively reduces the network transmission delay and guarantees the fast transmission of network information.

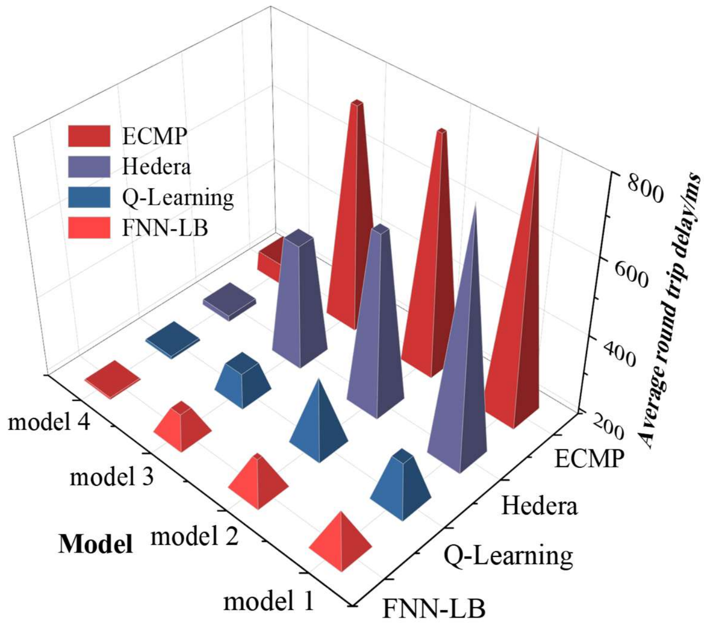


Fig. 9. Average round trip delay of mice flow

2) Packet loss rate of the mouse stream. The packet loss rate of this experiment is measured by the packet loss rate of the rat stream during the experiment time, and the packet loss rate of the rat stream is shown in Fig. 10. The optimized path selection algorithm for propagating information based on FNN-LB controls the rat flow packet loss rate below 0.004%, which well guarantees the propagation of network information.The rat flow packet loss rates of ECMP, Hedera, Q-Learning and FNN-LB algorithms for the four models are on average 0.0139%, 0.0106%, 0.0072% and 0.0022%, with the FNN-LB algorithm reducing it by 0.0050% to 0.0117%.

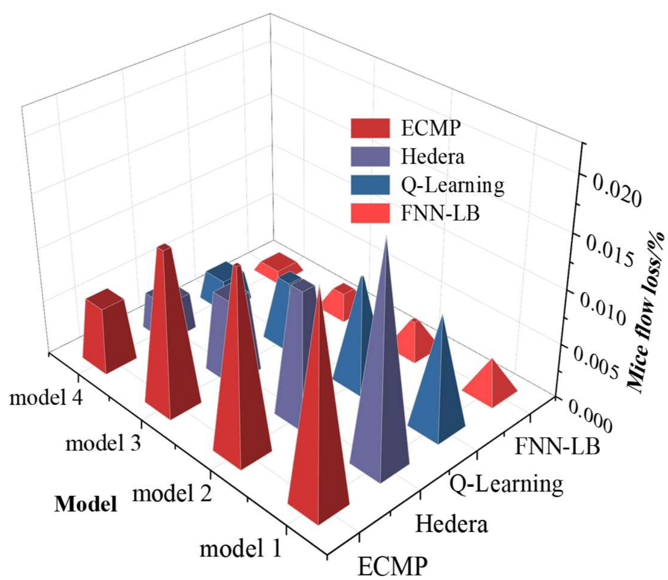


Fig. 10. Loss rate of mice flow

5. Conclusion

Along with the development of cloud computing and related businesses, the amount of propagated information in the network increases rapidly. In order to realize the optimal distribution of network propagation information, the study designs MT-LSTM-based traffic prediction algorithm and feed-forward neural network-based dynamic multipath load balancing algorithm (FNN-LB) for optimal path selection of propagation information. The traffic prediction and data flow efficiency improvement effects of the method are analyzed through experiments. The main results are as follows:

1) The MT-LSTM model has a faster convergence speed, and its traffic prediction has a smaller error, with an MSE value of only 0.573%, and the RMSE value is reduced by 2.682% compared with the LSTM model, which provides a higher prediction accuracy of the network propagation information traffic, and contributes to the overall accuracy of the optimized path selection strategy for propagation information.

2) The FNN-LB-based propagation information optimization path selection algorithm can select appropriate information propagation scheduling paths according to the real-time network state, effectively reducing the number of idle links and overloaded links, thus increasing the network throughput to a certain extent (2.34%~10.35%), improving link utilization, and controlling most of the bandwidth utilization of the link between 10% and 80% . At the same time, this traffic scheduling strategy also reduces the first packet round-trip delay and packet loss rate of the rat flow, and the first packet round-trip delay is reduced by more than 12.58%, which guarantees the efficient transmission of the first packet of the rat flow, and at the same time, reduces the average network delay and packet loss rate, and realizes the multi-objective optimization of the network performance, and it can achieve the research study to improve the utilization of the information resources of the network propagation, to reduce network transmission delay, and to guarantee the network transmission Objective.

In summary, the dynamic scheduling scheme for dissemination information data proposed in this paper based on deep neural network realizes the simultaneous guarantee of the transmission quality of mouse and elephant streams, avoids network congestion as much as possible, and improves the efficiency of the data flow of the overall network service.

References

[1] Apuke, O. D., & Omar, B. (2021). Fake news and COVID-19: modelling the predictors of fake news sharing among social media users. Telematics and Informatics, 56, 101475.

[2] Bokoh, M. A., Bello, M. M., & Idowu, A. A. (2022). Use of Social Media Platforms for Dissemination of Information and Creating Awareness about Library Resources and Services among Students in Lagos State University, Nigeria. Library Philosophy & Practice.

[3] Goel, A., & Gupta, L. (2020). Social media in the times of COVID-19. JCR: Journal of Clinical Rheumatology, 26(6), 220-223.

[4] Imanberdi, A., Lira, L., Aitolkyn, K., Leila, R., Abitova, G., Aigerim, B., ... & Assem, B. (2023). Assessment of the main features of the model of dissemination of information in social networks. International Journal of Electrical & Computer Engineering (2088-8708), 13(6).

[5] Jiang, G., Liu, F., Liu, W., Liu, S., Chen, Y., & Xu, D. (2021). Effects of information quality on information adoption on social media review platforms: Moderating role of perceived risk. Data Science and Management, 1(1), 13-22.

[6] Kandhway, K. (2022, June). Using Genetic Algorithm to Optimize Information Dissemination. In 2022 IEEE World Conference on Applied Intelligence and Computing (AIC) (pp. 604-609). IEEE.

[7] Kapoor, K. K., Tamilmani, K., Rana, N. P., Patil, P., Dwivedi, Y. K., & Nerur, S. (2018). Advances in social media research: Past, present and future. Information Systems Frontiers, 20, 531-558.

[8] Korchovyi, M., & Khoshaba, O. (2024). Optimizing methods and software for effective information dissemination in social networks. Information technologies and automation–2024, 148.

[9] Leaning, M. (2019). An approach to digital literacy through the integration of media and information literacy. Media and communication, 7(2), 4-13.

[10] Lodhia, S., & Stone, G. (2017). Integrated reporting in an internet and social media communication environment: conceptual insights. Australian Accounting Review, 27(1), 17-33.

[11] Pathak, S. J., & Patel, M. B. (2022). Farmers perception about print media in agricultural information dissemination: A review. Bhartiya Krishi Anusandhan Patrika, 37(4), 339-342.

[12] Rabin, B. A., & Brownson, R. C. (2017). Terminology for dissemination and implementation research. Dissemination and implementation research in health: Translating science to practice, 2, 19-45.

[13] Shonhe, L. (2017). A literature review of information dissemination techniques in the 21st century era. Library Philosophy and Practice (e-journal), 1731.

[14] Zhang, X., Wen, D., Liang, J., & Lei, J. (2017). How the public uses social media wechat to obtain health information in china: a survey study. BMC medical informatics and decision making, 17, 71-79.

[15] Soleimani, H., & Balivi, F. (2024). Optimizing Selective Dissemination of Information: Leveraging Genetic Algorithms for Enhanced Content Personalization. InfoScience Trends, 1(1), 8-12.

[16] Wu, Q., & He, L. (2021, November). Network information dissemination model and development analysis under new media environment. In 2021 2nd International Conference on Information Science and Education (ICISE-IE) (pp. 54-57). IEEE.

[17] Xinghua, D., Xiaojie, P., & Lei, W. (2022). The network community structure, information dissemination and cognitive proximity of venture capital. Science Research Management, 43(3), 134.

[18] Xu, Z., & Zhang, C. (2022). The dissemination effect of human-computer interactive advertising news—Using the theory of media audience and emotion management. Frontiers in Psychology, 13, 959732.

[19] Shi, J., Hu, P., Lai, K. K., & Chen, G. (2018). Determinants of users' information dissemination behavior on social networking sites: An elaboration likelihood model perspective. Internet Research, 28(2), 393-418.

[20] Wang, G., Wang, Y., Liu, K., & Li, J. (2019). Multidimensional influencing factors of public opinion information dissemination in social media: Evidence from Weibo dataset. International Journal of Modern Physics B, 33(31), 1950375.

[21] Al-Oraiqat, A. M., Ulichev, O. S., Meleshko, Y. V., AlRawashdeh, H. S., Smirnov, O. O., & Polishchuk, L. I. (2022). Modeling strategies for information influence dissemination in social networks. Journal of Ambient Intelligence and Humanized Computing, 13(5), 2463-2477.

[22] Yang, B., Zhang, R., Cheng, X., & Zhao, C. (2023). Exploring information dissemination effect on social media: an empirical investigation. Personal and Ubiquitous Computing, 27(4), 1469-1482.

[23] Fursov, D. V., Krylatov, A. Y., & Svirkin, M. V. (2024). Application of optimization methods in the problem of information dissemination in mass media. Applied Mathematics and Control Sciences, (1), 139-159.

[24] Liu, Y., Zhang, P., Shi, L., & Gong, J. (2023). A Survey of Information Dissemination Model, Datasets, and Insight. Mathematics, 11(17), 3707.

[25] Wang, X., Ning, Z., Hu, X., Wang, L., Hu, B., Cheng, J., & Leung, V. C. (2018). Optimizing content dissemination for real-time traffic management in large-scale internet of vehicle systems. IEEE Transactions on Vehicular Technology, 68(2), 1093-1105.

[26] Gong, Y. C., Wang, M., Liang, W., Hu, F., & Zhang, Z. K. (2023). UHIR: An effective information dissemination model of online social hypernetworks based on user and information attributes. Information Sciences, 644, 119284.