Hindawi
Security and Communication Networks
Volume 2020, Article ID 8857564, 6 pages
https://doi.org/10.1155/2020/8857564

Research Article

A Prediction Approach for Video Hits in Mobile Edge Computing Environment

Xiulei Liu,[1,2] **Shoulu Hou**,[1,2] **Qiang Tong**,[1,2] **Xuhong Liu**,[1,2] **Zhihui Qin**,[1,2] **and Junyang Yu**[3]

[1]*Beijing Advanced Innovation Center for Materials Genome Engineering, Beijing Information Science and Technology University, Beijing 100101, China*
[2]*Laboratory of Data Science and Information Studies, Beijing Information Science and Technology University, Beijing 100101, China*
[3]*Software School, Henan University, Kaifeng 475001, China*

Correspondence should be addressed to Junyang Yu; jyyu@henu.edu.cn

Received 13 August 2020; Revised 12 September 2020; Accepted 27 October 2020; Published 17 November 2020

Academic Editor: Xiaolong Xu

Smart device users spend most of the fragmentation time in the entertainment applications such as videos and films. The migration and reconstruction of video copies can improve the storage efficiency in distributed mobile edge computing, and the prediction of video hits is the premise for migrating video copies. This paper proposes a new prediction approach for video hits based on the combination of correlation analysis and wavelet neural network (WNN). This is achieved by establishing a video index quantification system and analyzing the correlation between the video to be predicted and already online videos. Then, the similar videos are selected as the influencing factors of video hits. Compared with the autoregressive integrated moving average (ARIMA) and gray prediction, the proposed approach has a higher prediction accuracy and a broader application scope.

1. Introduction

At present, smart device users spend more than 70% of the fragmentation time in the entertainment applications such as videos and films. The video content providers (e.g., Netflix) desire to know the future video view counts of all their videos, especially the new ones, to provide a better experience for consumers. In the era of the 5G-based mobile edge computing, the explosive increase of video resources requires placing multiple copies to the edge of the network for better performance [1–3]. The distributed model brings many problems for video service providers, such as how to keep the storage efficiency and improve the energy efficiency of storage [4, 5]. The key to solve these problems is to effectively manage data copies and data nodes [6–8]. The current popular cloud storage platforms generally use a static storage mechanism, that is, setting the number of copies before placing them, such as Google File System [9], Hadoop Distributed File System (HDFS) [10], and Amazon Dynamo [11]. The static placement of copies is easy to implement, but it may lead to unbalanced access. For example, it is found that 90.26% of the data in Yahoo's Hadoop Cluster can only be accessed within two days after constructing, 89.61% of the data from the last access to deletion do not exceed 10 days, and 40% of the data have a dormant period (not accessed) for more than 20 days [12].

The current research [13] shows that the migration and reconstruction of video copies is an effective means to improve the storage efficiency, and the prediction of the number of video hits is the prerequisite for migrating video copies. There are many data prediction and recommendation approaches [14, 15]; however, they do not consider the fine-grained granularity of every video copy and cannot provide the required information for migration and reconstruction of video copies. Additionally, the videos occupy a high proportion of storage space and have more rich attributes, and the trend of video hits is influenced by various factors, which are difficult to predict accurately. Based on the combination of correlation analysis and wavelet neural network (WNN), this paper proposes a new prediction approach for video hits by analyzing the correlation between the video to be predicted and already online videos, and selecting the similar videos as the influencing factors.

2. Related Work

2.1. Feature Analysis of Video Copies. A video copy covers a variety of attributes, such as news, teaching, and viewing, and it is the most representative type of data copies which are stored on the cloud. The existing hits prediction are coarse-grained (see Figure 1(a)), and they do not consider the fine-grained hits of every copy and cannot provide information for migration and reconstruction of video copies. The prediction approach that provides the hits of video copies is an urgent problem.

Figure 1(a) shows the trend of a long-timescale (in months) from March 2014 to February 2015. The reason for the smooth rising during the first few months is that "Transformers 4" released on June 2014 stimulates the previous series and even related science fiction series. From the short-timescale (in weeks) counterpart in Figure 1(b), it is found that the video hits have a certain periodicity and autocorrelation. This means that the video hits are affected by the hits of other similar videos. Therefore, the following are the general directions to follow to predict video hits: the short learning time of time series data and the small number of available parameters.

2.2. Existing Prediction Approaches. With more requirement of new entertainment, various prediction approaches for guaranteeing quality of service (QoS) have attracted increasing attention in recent years [16, 17]. Zhang et al. [18] proposed a covering-based quality prediction method for web services via neighborhood-aware matrix factorization. Qi et al. [15] proposed a novel privacy-aware data fusion and prediction approach for smart city industrial environment, which is based on the classic locality-sensitive hashing technique. Zhang et al. [19] proposed a distributed edge QoS prediction model with privacy-preserving for the edge computing networks. However, these works are from macroscopic point and cannot apply to the hits prediction of video copies which requires a micro perspective.

The autoregressive integrated moving average (ARIMA) model is based on the autocorrelation of time series, which is characterized by the fact that the first and the time series are broad and stable. Additionally, if the value of the individual data does not fluctuate up and down in the sequence mean value, ARIMA can do smooth processing of the original data through differential way. In this way, even if the data have a certain degree of fluctuation, the prediction accuracy can be achieved through the smooth processing. Therefore, ARIMA is suitable for prediction of the data with the flat trend and feature of linear wide stationary processes. It is often used in network traffic prediction [20, 21], while the traffic of each data copy has a more fine-grained granularity.

Gray prediction is a knowledge acquisition method with incomplete or uncertain data [22]. It processes the original data through the analysis of the difference degree of the changes in the system factors and predicts the future data by establishing the gray differential prediction model based on a small amount of information. Gray prediction model applies to the situation that the video copy is just launched into the market, which has little original data. These two methods seem to be feasible, but because of the video copy of the fluctuations in many factors, we analyze this video from the factors.

This paper considers the fact that the number of hits for each video is closely related to its similar videos. This is achieved by analyzing the principal components of the sources of the video viewing modes. For example, a systematic quality correlation model was proposed that described three different types of quality correlations between services [23]. Logically, there are some relevant video recommendations after watching a certain video on the web, and the recommendation and impact of the associated videos are the principal components of video-on-demand. By investigating and analyzing the Storm website, after a video is watched, the average viewing rates of the top three similar videos recommended by Storm are 47%, 30%, and 25%, respectively. The average value of the recommendation results comes from 200 videos which are randomly sampled from the Storm website. This means that when the total number of viewers remains stable, it is possible to infer the number of potential viewers of a certain video in the future, according to the current number of viewers of its similar videos. There exists delay during the process, and it is essential for intelligent analysis. This paper applies the wavelet neural network to predict future video hits. The wavelet-based neural network replaces the activation function of hidden nodes with wavelet function. In recent years, several researches applied the wavelet neural network model to predict network traffic [24], but the hits prediction of video copies is a more micro perspective. The key to solve this problem is to inversely deduce the videos that are used as prediction-relevant parameters, according to the video to be predicted.

2.3. Selection of Associated Videos. The choice of related video in this paper is divided into two steps: the first step is to select 12 videos that are similar to the video to be predicted; the second step further reduces the parameter dimension, from the similarity of the video selecting the highest degree of relevance of the four.

2.3.1. Similar Video Selection. Similar video selection is in the same type of videos through the establishment of vector space model (VSM) to calculate and select the level of the video, the degree of the audience, the type of video, the age of the audience, the influence of the producers, etc., and then refine and quantify the score between 0 and 100, as shown in Table 1.

Let m_1 and m_2 be the video objects to be compared, and $f_1, f_2, \ldots\ldots, f_n$ be the attributes of every object. The similarity

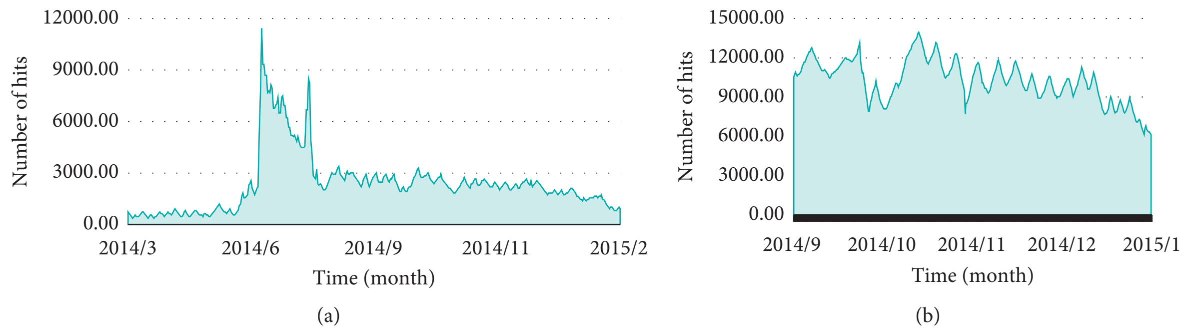

Figure 1: The hits trend of "Transformers 3." (a) The trend of "Transformers 3" from 2014.3 to 2015.2. (b) The trend of "Transformers" from 2014.9 to 2015.2.

Table 1: Video attribute rating scale.

	Production company	Actor level	The audience high school≤	Bachelor degree	≥Master's degree	Ages 20≤	20–30	30–50	≥50	Video rating
m_1	80	90	30	60	10	32	56	6	6	72
m_2	80	90	20	76	14	16	70	9	5	80
m_3	70	80	10	70	20	17	65	12	6	83
...	...	...	...	...	...	...	...	...	...	...

between m_1 and m_2 can be calculated by using the attributes of video objects. The values of the video attribute f_i corresponding to m_1 and m_2 are denoted by a_i and b_i, respectively. By using support vector machine (SVM), the similarity between m_1 and m_2, denoted by $\mathrm{Sim}(m_1, m_2)$, is calculated as follows:

$$\mathrm{Sim}(m_1, m_2) = \frac{m_1 \cdot m_2}{\|m_1\| \times \|m_2\|} = \frac{\sum_i (a_i \times b_i)}{\sqrt{\sum_i a_i^2 \times \sum_i b_i^2}}. \quad (1)$$

From equation (1), we can calculate the most similar 12 videos, in order to further reduce the dimension, and from the 12 videos to select the most relevant video as a prediction parameter.

2.3.2. Correlation Degree Analysis. Table 2 shows the hits of 6 sample videos within 10 days, where $x1$ is from 2014.10.26 to 2014.11.24, and the data of $x2, \ldots, x5$ cover the time span from 2014.10.20 to 2014.11.18. $x1$ is the video to be predicted, which can be obtained by the hits of other videos in the last week.

The calculation of the association degree can be divided into the following steps.

Step 1: standardize the data in Table 2, where x, y represent longitudinal data and horizontal data, respectively. The sample mean of j-th video is $\overline{Y}_j = (1/m)\sum_{i=1}^{m} Y_{ij}$ $(j = 1, 2, \ldots\ldots, n)$; through it, we can calculate the sample variance of j-th video: $S_j^2 = (1/m-1)\sum_{i=1}^{m}(Y_{ij} - \overline{Y}_j)^2$ $(j = 1, 2, \ldots\ldots, n)$; standardized form is $X_{ij} = (Y_{ij} - \overline{Y})/S_j$. After standardized calculation, we have

Table 2: Comparison on the video hits.

$x1$	$x2$	$x3$	$x4$	$x5$	$x6$
48101	26773	34708	849620	228982	5319
49052	27698	46100	824476	231698	4018
49702	27389	60668	822595	253113	4282
52146	26822	61768	743477	256318	4341
......	......	......	......	......	......
29694	86084	58727	236572	104088	3480

$$X = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2n} \\ \vdots & \vdots & & \vdots \\ X_{m1} & X_{m2} & \cdots & X_{mn} \end{bmatrix}. \quad (2)$$

Step 2: calculate the correlation matrix $R = (r_{ij})_{m \times m}$, $r_{ij} = \sum_{k=1}^{n} x_{ki} x_{kj} / (n-1)$, $(i, j = 1, 2 \ldots, m)$; then we can analyze the correlation between the videos after getting the correlation matrix, as shown in Table 3, in which the x1 is the video that needs to be predicted; $x2$, $x3$, $x4$, $x5$, $x6$ is the similar video that needs to be analyzed for the degree of change.

From 12 similar videos, select the correlation matrix and $x1$ closest to the four videos used as predictive video; the above matrix is the first batch to be compared with video $x1$; it is clear that $x4$, $x5$, and $x1$ are highly correlated with clicking playback. In this way, select the videos $x3$–$x5$ and use the current number of hits to predict the hits of video $x1$.

Table 3: Correlation matrix of videos.

	$x1$	$x2$	$x3$	$x4$	$x5$	$x6$
$x1$	1.0000	−0.4893	0.3744	0.8808	0.9149	0.3654
$x2$	−0.4893	1.0000	−0.0046	−0.3993	−0.4509	−0.1175
$x3$	0.3744	−0.0046	1.0000	0.0990	0.3364	0.3366
$x4$	0.8808	−0.3993	0.0990	1.0000	0.9322	0.0689
$x5$	0.9149	−0.4509	0.3364	0.9322	1.0000	0.0785
$x6$	0.3654	−0.1175	0.3366	0.0689	0.0785	1.0000

2.4. Wavelet Neural Network. Neural networks are often used to predict and analyze non-linear time series. In theory, neural network prediction accuracy can be achieved arbitrarily. But in practical application, it may meet many difficulties, such as the delineation of the structure of the neural network, training and learning process being too slow, and being trapped in local second-best in the optimization process. WNN combines the characteristics of wavelet analysis and neural network. It replaces the neurons in the neural network with wavelet neurons, replaces the Sigmoid in the neural network with wavelet functions (as activation function), and establishes the relationship between wavelet transform and network coefficients through affine transformation. The WNN has the following characteristics:

(1) High prediction accuracy due to strong learning ability and excellent function approximation ability.

(2) The fact that local optimum can be avoided as the shift factor and scaling factor of the network are determined in advance.

(3) High learning and training speed as wavelet function as an activation function is easy to implement.

The WNN has three layers: input layer, hidden layer, and output layer, as shown in Figure 2. The output layer adopts the linear output. The neurons of the input layer are (x_1, x_2, . . ., x_m), the hidden layer has K neurons, and the output layer has N neurons. In this case, since the number of associated videos is 4, there are 4 related parameters as the basis for prediction and the input neuron selection is 4. In the set of daily visits, it is found that the visits are recorded in the unit of day; the visit cycle is 7 days. Then, the number of neurons used in the middle of the hidden layer is set to 7, and the output layer is 7. That is why this case uses 4-7-7 structure neural network. $h_k(x)$ is the wavelet basis function, instead of the previous activation function Sigmoid.

Let w_{ij} denote the weights of neurons from layer $p-1$ to layer p, a_r^m denote the r-th input of neuron i in layer p, φ_p denote the transfer function of layer p, and b_r^p denote the corresponding output of the layer.

$$a_r^p = \sum_i w_{ij}^p b_r^{(p-1)}, \tag{3}$$

$$b_r^p = \varphi_p\left(a_r^m\right). \tag{4}$$

Since the case is designed in a three-tier network, $b_r^1 = x_{r-j+1}$, $b_r^3 = \widehat{x}_{r+1}$ are the transfer functions in the hidden layer. This case is called "Morlet wavelet," which is given by

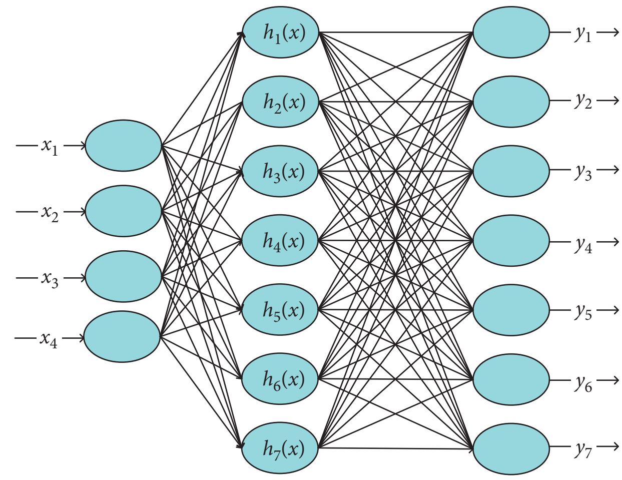

Figure 2: The hierarchy diagram of WNN.

$$\varphi(\mu) = \cos(1.75\mu)e^{\left(-\mu^2/2\right)}. \tag{5}$$

Substituting (5) into (3) and (4), we get

$$a_r^2 = \sum_{i=1}^{m} w_{ij}^2 x_{r=j+1}, \tag{6}$$

$$b_r^2 = \varphi_2\left(\frac{a_r^2 - b_j}{a_j}\right). \tag{7}$$

According to (6) and (7), we can conclude that the video prediction on time series is

$$x_{r+1} = \sum_{i=1}^{K} b_r^2 w_j^3 = \sum_{j=1}^{K} \varphi_2\left(\frac{a_r^2 - b_j}{a_j}\right). \tag{8}$$

Given the input and output samples of group, the error function can be expressed as

$$E = \sum_{P=1}^{P} E^P = \frac{1}{2P}\sum_{P=1}^{P}\sum_{n=1}^{N}\left(d_n^P - y_n^P\right), \tag{9}$$

where d_n^P is the expected output of the n-th node and y_n^P is the actual output of the n-th node. w_k, b_k, and a_k are constantly adjusted to minimize the error. When the error is less than the given value, the program will end, and an appropriate prediction value can be calculated.

For a series of videos that have similar and stable attributes, the proposed approach can achieve reasonable prediction results. However, for certain videos that have a worse or better reputation than other videos in the series, the proposed approach may produce a biased prediction result. This is because a potentially unbalanced reputation has affected the final results.

2.5. Performance Evaluation. As the actual video copy, if the prediction granularity is too low, such as one day, it does not make much sense, because it is impossible for the video copy

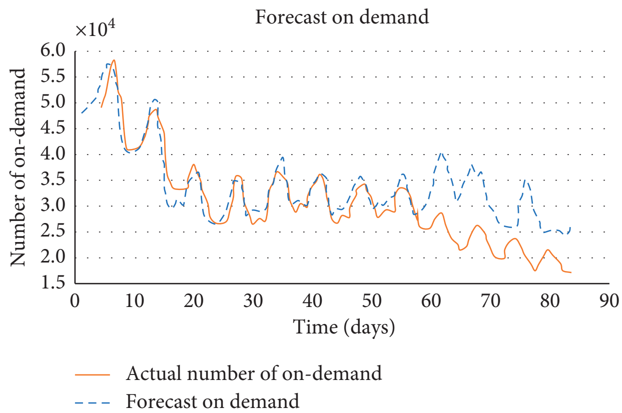

Figure 3: Prediction of ARIMA approach (56–84 is the actual prediction).

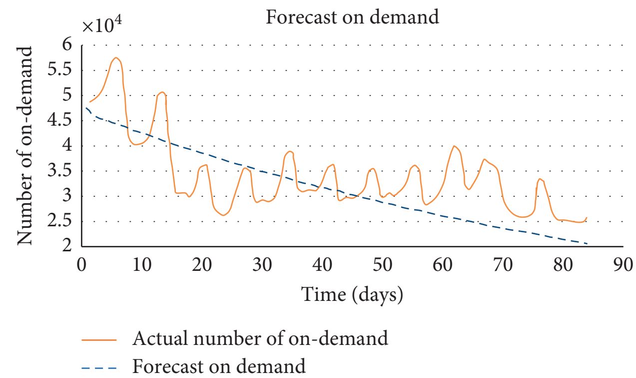

Figure 4: Prediction of gray approach (56–84 is the actual prediction).

to undergo frequent evaluation migration with a 24-hour time unit. If the prediction granularity is too long, such as in the unit of month, the weekly trends of a video copy cannot be timely captured. So, this experiment is expected to have a length of weeks and data collection is based on days, the estimated collection of 84 days of data. The number of targets to be tested is from 2014.10.26 to 2015.1.17, and the video data as the influencing factor are from 2014.10.20 to 2015.1.11, the first 56 days of the two sides are used as training data, and the last 28 days of data are used as the test data. The experiment runs on 64-bit Windows 7 Professional with 10 GB of RAM and 2.1 GHz Intel Core i3 processor and uses MATLAB R2014a to conduct the simulation and numerical analyses. The neural network is designed to be 4-7-7 structure, and the output is 7-node data.

From Figure 3, it can be seen that ARIMA through differential algorithm fits the time series data well before prediction, but it is not accurate in grasping the trend of the data. Figure 4 shows that the gray prediction can predict the general trend of the data but has a large error range. In terms of the change trend and prediction accuracy, the performance of the proposed approach exhibits the optimal results, as shown in Figure 5.

If it is predicted after a week, it will become a training set and then forecast the way of the next week. The time granularity of each prediction is not the same, which is 7 days, 14 days, and 28 days, respectively. As can be seen from Table 4, if the time granularity for prediction is 1 week or 4 weeks, the proposed approach is the most accurate and far higher than those of ARIMA and gray. If the time granularity for prediction is two weeks, the accuracies of the three prediction methods are comparable. In the proposed approach, the histories of hits of the similar video are used as the influencing factors. Therefore, it can be inferred that the prediction approach based on the combination of the correlation analysis and WNN has better practical effect than the alternatives.

When applying this method to several other types of videos, the result is similar to the above case. The average prediction accuracy of the proposed approach is 10% higher than that of ARIMA and 5–7% higher than that of gray prediction.

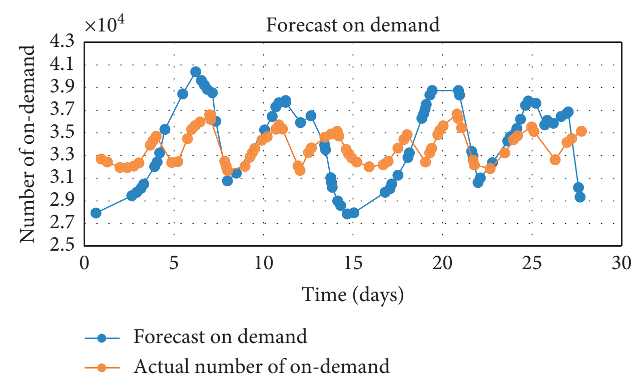

Figure 5: Prediction of the proposed approach.

Table 4: Comparison of the error rates of different approaches.

	Forecast for 7 days (%)	14 days (%)	28 days (%)
ARIMA	16.7	18.01	24.81
Gray	18.28	16.11	20.60
WNN	13.85	16.49	14.11

From the above analysis, each prediction approach has its own advantages and disadvantages. ARIMA has certain advantages if the video enters a certain life cycle, which have the relatively flat change trend and the feature of linear wide stationary processes. But if the change trend of hits is gentle, it has little significance for migrating video copies.

3. Conclusions

This paper proposes a new prediction approach for video hits based on the combination of correlation analysis and WNN. This is achieved by establishing the video index quantification system and analyzing the correlation between the video to be predicted and already online videos. Then, the similar videos are selected as the influencing factors of video hits. Compared with the ARIMA and gray prediction, the proposed approach has a higher prediction accuracy and a broader application scope.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Authors' Contributions

Xiulei Liu and Junyang Yu proposed the overall idea of this manuscript. Shoulu Hou and Xuhong Liu designed the experimental plan. Qiang Tong and Zhihui Qin wrote and revised the manuscript. All authors have contributed to this research work. All authors have read and approved the final manuscript.

Acknowledgments

This work was supported in part by the National Key R&D Program of China (No. 2018YFC0830202); supported in part by Qin Xin Talents Cultivation Program, Beijing Information Science and Technology University (2020); supported in part by Construction Project of Innovative Scientific Research Platform for Edge Computing (No. 2020KYNH105); and supported in part by the Opening Foundation of State Key Laboratory of Digital Publishing Technology.

References

[1] X. Xu, X. Zhang, X. Liu, J. Jiang, L. Qi, and M. Z. A. Bhuiyan, "Adaptive computation offloading with edge for 5G-envisioned internet of connected," *IEEE Transactions on Intelligent Transportation Systems*, 2020.

[2] Y. Chen, N. Zhang, Y. Zhang, and X. Chen, "Dynamic computation offloading in edge computing for internet of things," *IEEE Internet of Things Journal*, vol. 6, no. 3, pp. 4242–4251, 2019.

[3] J. Huang, J. Liang, and S. Ali, "A simulation-based optimization approach for reliability-aware service composition in edge computing," *IEEE Access*, vol. 8, pp. 50355–50366, 2020.

[4] Y. Chen, Y. Zhang, Y. Wu, L. Qi, X. Chen, and X. Shen, "Joint task scheduling and energy management for heterogeneous mobile edge computing with hybrid energy supply," *IEEE Internet of Things Journal*, vol. 7, no. 9, p. 8419, 2020.

[5] J. Huang, C. Zhang, and J. Zhang, "A multi-queue approach of energy efficient task scheduling for sensor hubs," *Chinese Journal of Electronics*, vol. 29, no. 2, pp. 242–247, 2020.

[6] X. Xu, R. Mo, F. Dai, W. Lin, S. Wan, and W. Dou, "Dynamic resource provisioning with fault tolerance for data-intensive meteorological workflows in cloud," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 9, pp. 6172–6181, 2020.

[7] J. Li, T. Cai, K. Deng, X. Wang, T. Sellis, and F. Xia, "Community-diversified influence maximization in social networks," *Information Systems*, vol. 92, pp. 1–12, 2020.

[8] X. Xu, S. Fu, W. Li, F. Dai, H. Gao, and V. Chang, "Multi-objective data placement for workflow management in cloud infrastructure using NSGA-II," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 4, no. 5, p. 605, 2020.

[9] G. Ghemawat, H. Gobioff and S. T. Leung, The Google file system," in *Proceedings of the Nineteenth ACM symposium on Operating systems principles*, pp. 29–43, Landing NY USA, October 2003.

[10] K. Shvachko, H. Kuang, S. Radia, and R. Chansler, "The hadoop distributed file system," in *Proceedings of the 2010 IEEE 26th symposium on mass storage systems and technologies (MSST)*, pp. 1–10, IEEE, Tahoe, NV, USA, May 2010.

[11] G. DeCandia, D. Hastorun, M. Jampani et al., "Dynamo," *ACM SIGOPS Operating Systems Review*, vol. 41, no. 6, pp. 205–220, 2007.

[12] R. T. Kaushik and M. Bhandarkar, "Greenhdfs: towards an energy-conserving, storage-efficient, hybrid hadoop computer cluster," in *Proceedings of the USENIX Annual Technical Conference*, vol. 109, p. 34, Boston, MA, USA, June 2010.

[13] A. Higai, A. Takefusa, and H. Nakada, "A study of effective replica reconstruction schemes at node deletion for HDFS," in *Proceedings of the 2014 14th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing*, pp. 512–521, IEEE, Chicago, IL, USA, May 2014.

[14] L. Qi, Q. He, F. Chen, X. Zhang, W. Dou, and Q. Ni, "Data-driven web apis recommendation for building web applications," *IEEE Transactions on Big Data*, 2020.

[15] L. Qi, C. Hu, X. Zhang et al., "Privacy-aware data fusion and prediction with spatial-temporal context for smart city industrial environment," *IEEE Transactions on Industrial Informatics*, p. 1, 2020.

[16] Y. Chen, N. Zhang, Y. Zhang, X. Chen, W. Wu, and X. S. Shen, "TOFFEE: task offloading and frequency scaling for energy efficiency of mobile devices in mobile edge computing," *IEEE Transactions on Cloud Computing*, 2019.

[17] J. Huang, S. Li, and Y. Chen, "Revenue-optimal task scheduling and resource management for IoT batch jobs in mobile edge computing," *Peer-to-Peer Networking and Applications*, vol. 13, pp. 1776–1787, 2020.

[18] Y. Zhang, K. Wang, Q. He et al., "Covering-based web service quality prediction via neighborhood-aware matrix factorization," *IEEE Transactions on Services Computing*, 2019.

[19] Y. Zhang, J. Pan, L. Qi, and Q. He, "Privacy-preserving quality prediction for edge-based IoT services," *Future Generation Computer Systems*, vol. 114, pp. 336–348, 2021.

[20] M. Lippi, M. Bertini, and P. Frasconi, "Short-term traffic flow forecasting: an experimental comparison of time-series analysis and supervised learning," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 2, pp. 871–882, 2013.

[21] Y. Yu, J. Wang, M. Song, and J. Song, "Network traffic prediction and result analysis based on seasonal ARIMA and correlation coefficient,"vol. 1, pp. 980–983, in *Proceedings of the 2010 International Conference on Intelligent System Design and Engineering Application*, vol. 1, pp. 980–983, IEEE, Changsha, China, October 2010.

[22] S. Liu, M. Hu, F. Jeffrey, and Y. Yang, "Progress of grey system models," *Transactions of Nanjing University of Aeronautics and Astronautics*, vol. 29, no. 2, pp. 103–111, 2012.

[23] Y. Zhang, G. Cui, S. Deng, F. Chen, Y. Wang, and Q. He, "Efficient query of quality correlation for service composition," *IEEE Transactions on Services Computing*, 2018.

[24] N. M. Hindoriya, S. N. Singh, and S. K. Singh, "An adaptive wavelet neural network-based energy price forecasting in electricity markets," *IEEE Transactions on Power Systems*, vol. 23, no. 3, pp. 1423–1432, 2008.