

Retraction

Retracted: The Application of AI-Based Technology in Computer Network Operation and Maintenance

Mobile Information Systems

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Li, "The Application of AI-Based Technology in Computer Network Operation and Maintenance," *Mobile Information Systems*, vol. 2022, Article ID 2971393, 10 pages, 2022.

Research Article

The Application of AI-Based Technology in Computer Network Operation and Maintenance

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As an emerging IT technology, artificial intelligence has unique advantages in data extraction and data processing. In this paper, an artificial intelligence search method based on the K-means algorithm is proposed. According to the similarity between data samples, the samples are divided into many different categories. The ARIMA algorithm is used to perform regression analysis on the traffic data, and a Boosting model is established to improve the time series prediction accuracy. And, we use the relative distance between elements to represent the degree of dissimilarity of different types of variables. It can process massive data in a short time and obtain user behavior information. A large number of experiments show that the method proposed in this paper can complete information search more effectively and complete information classification quickly.

1. Introduction

The current network operation environment presents high speed, high flexibility, and high adaptability conditions. [1].

Traditionally, computer network management relies on managers using management software to regulate the condition of the network system. Due to the large workload, heavy tasks, and personnel load of network management, the application of artificial intelligence technology can eliminate many trivial manual operations and generally improve people's lives and the timeliness of network management. Due to the increasing amount of data generated in people's working life and the complexity of data sources, network monitoring is less effective and control is insufficient as far as traditional computer network technologies are concerned [2]. The number of web pages is even higher, reaching 315.5 billion [3]. These applications and websites handle a large amount of business every day, so IT (information technology) operations and maintenance play a very critical role in ensuring the healthy and stable operation of business systems in these industries.

Computer networks contain a large amount of unknown, cumbersome, and ambiguous data covering many domains, which would be very difficult to handle with

traditional computer networks. The data used in the AI analysis process do not need to be completely accurate, and by simulating human thought patterns, it can flexibly analyze and handle fuzzy problems. The costs incurred in data center operations are increasing today in order to meet the growing demand in various fields. The main algorithm used in AI is the control algorithm, which has a higher computing speed and consumes fewer resources, which can effectively reduce the costs incurred during operations [4].

The early IT operation and maintenance method is relatively backward and is manually completed by the personnel. Enterprises urgently need an efficient, fast, accurate, and low-cost operation and maintenance to meet the growing demand for digital operations and maintenance, so the combination of Internet, AI, and operations and maintenance of AIOps (AI for IT Operations, intelligent operations, and maintenance) was born and the concept of intelligent operations and maintenance was first proposed by Gartner in 2016 [5].

In some enterprises, the task of network operation and maintenance may even go through layers of dispatch and the final work efficiency is very low. This iterative discrete operation and maintenance model seriously restricts the efficiency and timeliness of network operation and

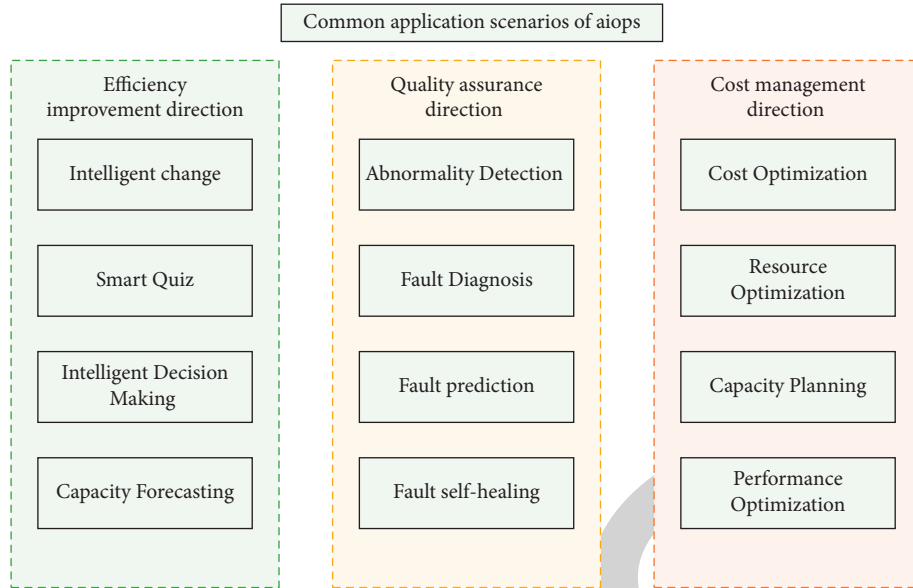


FIGURE 1: AIOps scenario.

maintenance, staff work more passively, enterprises focus only on the management of personnel, ignoring the impact of other factors on the network, and it is more difficult to start normal network operation and maintenance work [6, 7].

The current stage of network traffic contains a huge amount of information; how to extract and analyze the useful security information from it is the top priority to solve the network operation and maintenance problems. Only the timely and effective mining, analysis, and utilization of security data can sharply catch the abnormalities in data traffic and can effectively predict, analyze, and defend against security risks [8, 9].

This paper proposes an AI search method based on the K-means algorithm, which divides samples into many different categories according to the similarity between data samples. In the era of big data, the integration of artificial intelligence technology and computer network can greatly increase measurement time and improve information security. With the passage of time, the rapid development of computing network is also facing difficulties. The operation strategy of artificial intelligence in the network needs continuous exploration and research to improve the intelligence level of the network.

2. Related Work

Traditional operation and maintenance methods are time-consuming and labor-intensive, and the mode of relying on manual analysis can no longer cope with the performance monitoring requirements of complex networks and massive devices [10]. How to monitor massive network performance indicators in real time, reduce manual involvement, and achieve early fault detection with higher efficiency is a key issue that operators need to address in the process of industry competition and O&M transformation [11].

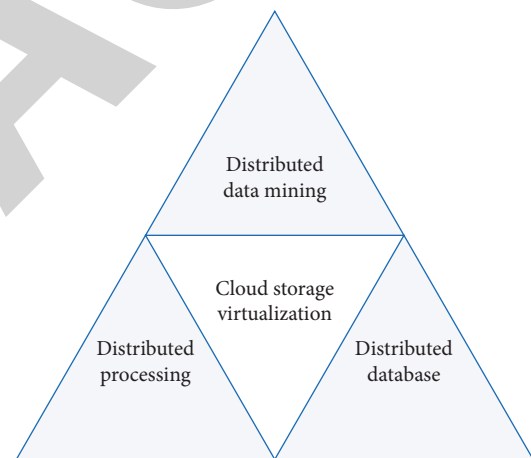


FIGURE 2: Relationship between big data and cloud computing.

In recent years, the theoretical foundation of machine learning algorithms has become more and more complete. Among them, time series prediction models have received attention from many researchers and have been widely used in many fields such as engineering technology, medical engineering, economics, and network communication with good results. The traditional modeling methods include linear regression, differential autoregressive moving average model (ARIMA), cubic exponential smoothing (Holt-Winters), Kalman filter, etc. [12]. These models have clear concepts and relatively advanced development, and there are many forecasting examples at home and abroad. With the development of AI technology, time series forecasting methods based on neural networks have been rapidly developed [13].

At present, domestic and foreign research in the field of operations and maintenance is not synchronized; foreign companies have been established for intelligent operations and maintenance of this piece of comprehensive research,

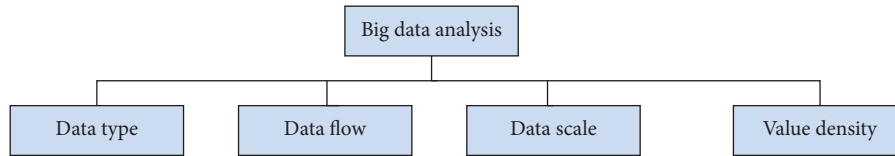


FIGURE 3: Characteristics of big data.

but only a small number of large enterprises in China, such as BAT and Huawei, begin to explore the field of intelligent operations and maintenance [14]. Therefore, intelligent operation and maintenance research must be on the agenda, and more experts and enterprises should pay attention to this, so that there is hope in the field of intelligent operation and maintenance to lead the world, or even like Huawei 5G as the industry leader to develop the corresponding standards [15, 16].

In 2018, the white paper “Enterprise AIOps Implementation Recommendations,” jointly sponsored and developed by the Efficient Operations Community and the AIOps Standards Working Group (with members from BAT, 360, Jingdong, Huawei, and other well-known enterprises), provides an overall introduction to AIOps, and the book details common application scenarios for AIOps and key technologies for implementation. [17]. The main task of operation and maintenance engineers is to be able to extract intelligent demand analysis from the technical operation of the business, and according to the standard data format; the main task of operation and maintenance development engineers is to be responsible for the development of intelligent operation and maintenance platform-related functions and modules [18].

The common application scenarios of AIOps can be divided into three directions, as shown in Figure 1.

In the direction of efficiency improvement, it can be divided into intelligent change, intelligent Q&A, intelligent decision, and capacity prediction and in the direction of quality assurance, it can be divided into anomaly detection, fault diagnosis, fault prediction, and fault self-healing; in the direction of cost management, it can be divided into cost optimization, resource optimization, capacity planning, and performance optimization. In different directions, AIOps business is oriented to different focuses to respond to the differentiated needs of different enterprises, with the overall goal of maximizing the comprehensive benefits of quality, cost, and efficiency [19, 20].

2.1. Big Data Analytics Technology. Big data analytics is currently the key applicable area of AI, and this technology can greatly improve the scale of storing, managing, and analyzing data. As can be seen from Figure 2, big data analytics is mainly realized through the combination of distributed data mining, processing, and data storage with cloud storage and virtualization [21].

Big data and cloud computing, as the right and left arms of AI technology in the data field, can improve the decision-

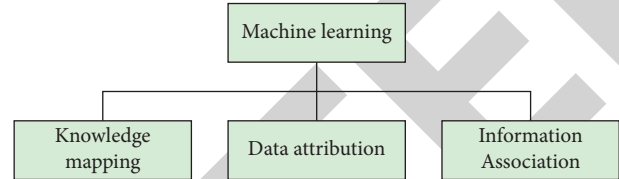


FIGURE 4: Application of ML.

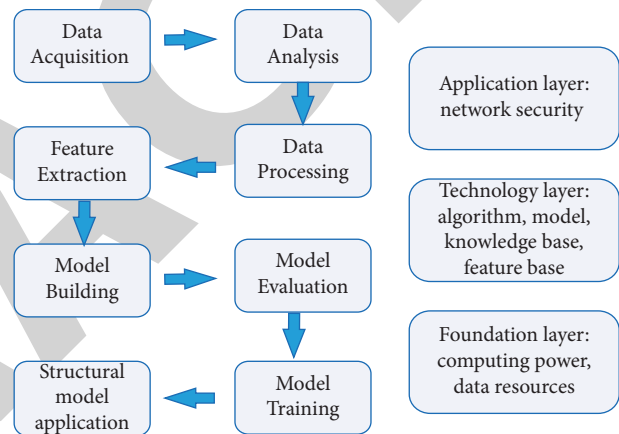


FIGURE 5: Architecture of AI.

making power, insight, and process optimization ability of network operation and maintenance. As can be seen from Figure 3, big data analysis has four characteristics: multiple data types, fast data flow, large data scale, and low-value density.

2.2. Machine Learning (ML). ML is also another important area of AI, which gives the characteristics of computer intelligence and has application areas in all aspects of AI. From Figure 4, ML can be used for intelligent operation and maintenance to help dig deeper into the textual information of traffic, build a complete knowledge base system from six levels of knowledge acquisition, compilation, application, update, data utilization, and intelligence, and promote and unify the knowledge graph [22].

Then, the intelligent operation and maintenance system can refine the association and bearing relationship between data in the information system and use the real meaning and interrelationship of data presented in the knowledge graph to significantly improve the storage and retrieval ability of the computer [23–25].

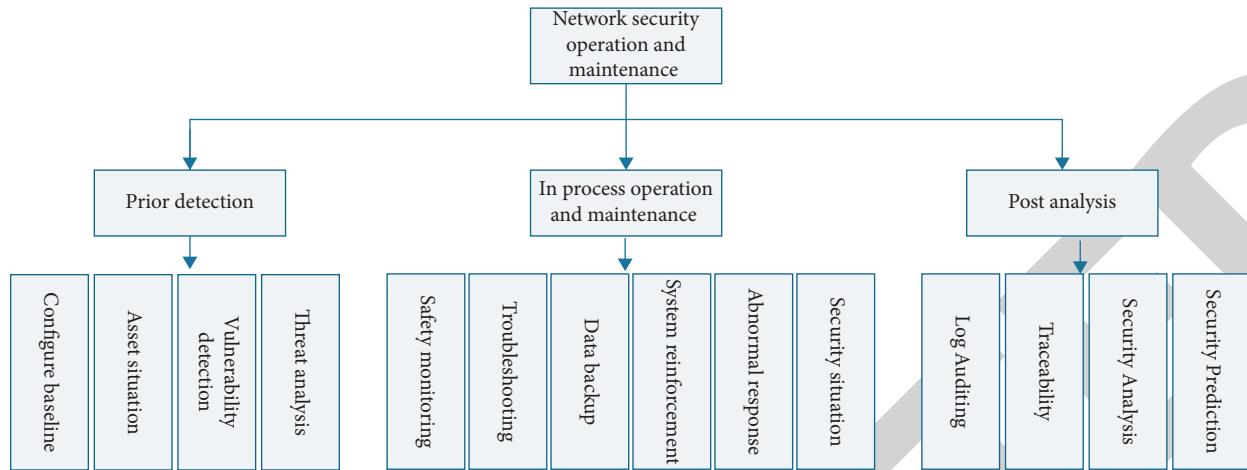


FIGURE 6: Network security operations and maintenance services architecture.

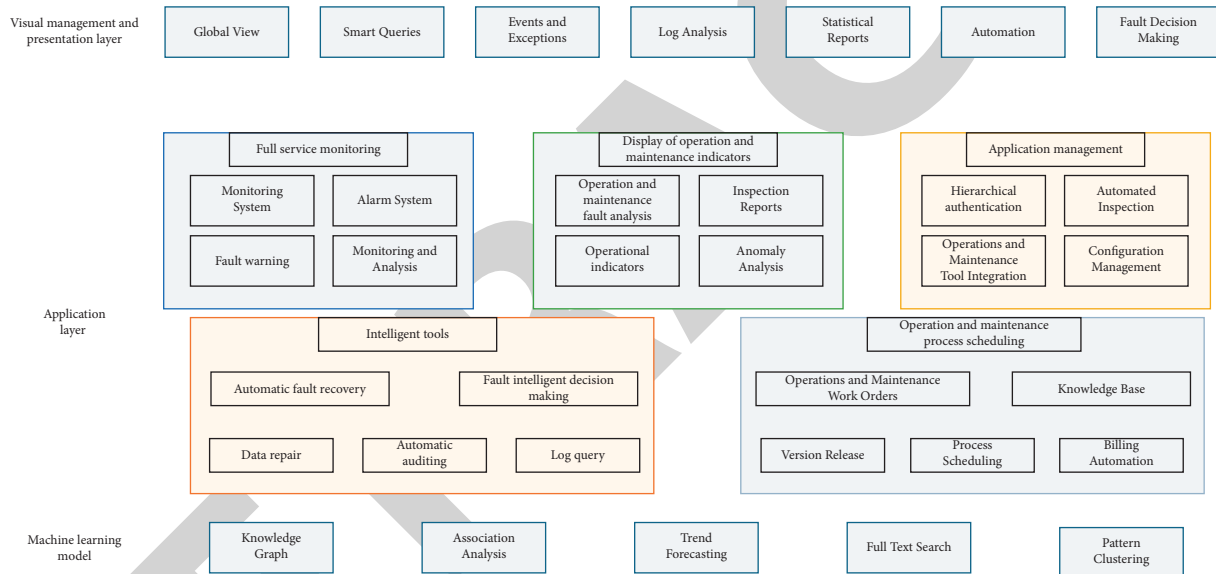


FIGURE 7: Functional framework of intelligent operation and maintenance platform.

3. Methodology

The architecture of AI technology is generally divided into three layers. As can be seen from Figure 5, the foundation layer is used for data acquisition, analysis, and processing, which contains the computing power and data resource acquisition capability; the technology layer includes algorithms, and models.

Large enterprises contain many divisional organizations and should adapt the concept of centralized operation and maintenance and adapt cloud-loaded computing units to realize reasonable network security operation and maintenance services. Network security O&M services can be divided into three stages: before, during, and after, and the advantages of AI technology can be played in the whole life cycle of network security O&M services to realize intelligent operation, as shown in Figure 6.

The functional framework of the intelligent operation and maintenance platform is shown in Figure 7. Traditional computer network maintenance has low efficiency, long cycle time, and difficulty in guarantee the quality, which cannot keep up with the needs of users. Among them, intelligent fault tracing technology can filter and filter classified alarm information, extract fault characteristics, and conduct AI learning based on KPI indicators and fault handling experience to form a fault diagnosis database and trace faults according to the relationship between alarm information.

The specific process is shown in Figure 8. AI, supported by massive data, can be used as a carrier for information distribution, establish an intelligent database, collect user behavior information for learning and feedback, and then perform expected analysis for different environments to provide users with intelligent decision specifications.

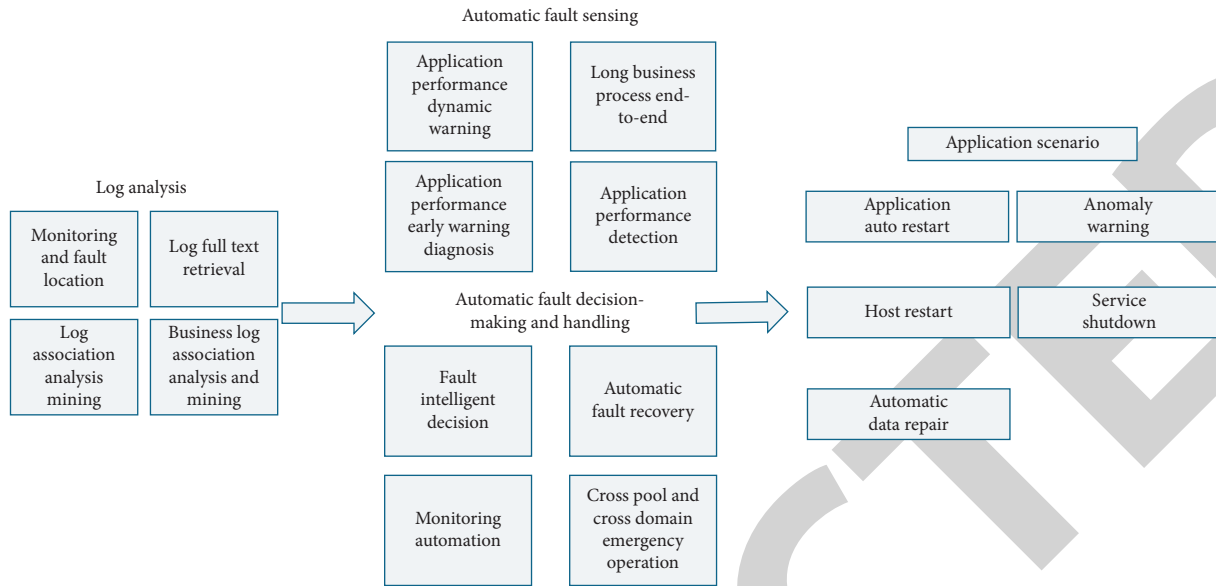


FIGURE 8: Flow chart of fault-aware processing.

3.1. Computer Network Management. In view of the popularity of intelligence and information technology, enterprises and various organizations and even people’s lives rely more and more on computer technology. The high integration of computer networks and AI technology can improve the operation efficiency of databases, greatly improve the efficiency of network management, reduce management difficulties, and provide decision-making directions for enterprise work. Based on this, *K*-means algorithm can be used to process massive data in a short period of time, obtain user behavior information, analyze people’s needs to provide reasonable optimization solutions, and improve computer network management. *K*-means algorithm is widely used in the direction of ML and data mining.

It is a typical unsupervised learning algorithm, which divides samples into many different categories according to the similarity between data samples. The flow of the *K*-means algorithm is shown in Figure 9.

In general, we use the relative distance between elements to express the dissimilarity of different types of variables, and several common distance calculation methods are described in the following.

3.1.1. Euclidean Distance. Euclidean distance is the geometric distance between the sample and the center of mass in Euclidean space, which has the characteristics of intuitive and interpretable; therefore, Euclidean distance is widely used in daily life.

3.1.2. Manhattan Distance. The Manhattan distance is the length of the projection of the line connecting two points on the coordinate axis in the right-angle coordinate system, and its distance is calculated.

The traditional *K*-means algorithm is tedious in steps and processes, and the *K*-means algorithm can be optimized. First, a sample is randomly selected from the data set as the

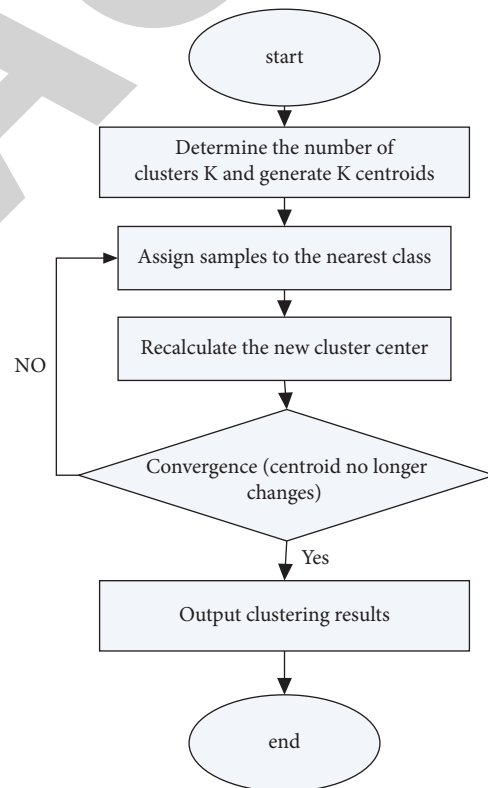


FIGURE 9: K-means algorithm flow.

initial center of mass μ_1 , $d(q_i, \mu_1)$, and the farthest sample point is selected as another center of mass μ_2 . Then, the distance between two centers of mass μ_1 and μ_2 is calculated $d(\mu_1, \mu_2)$, and the sample point q_j is selected according to the spatial three-dimensional geometry property; if $2 d(q_j, \mu_1) \leq d(\mu_1, \mu_2)$, then $d(q_j, \mu_1) \leq d(q_j, \mu_2)$; that is, the sample point q_j is closer to the center of mass μ_1 ; otherwise, it is closer to the center of mass μ_2 , and there is no need to

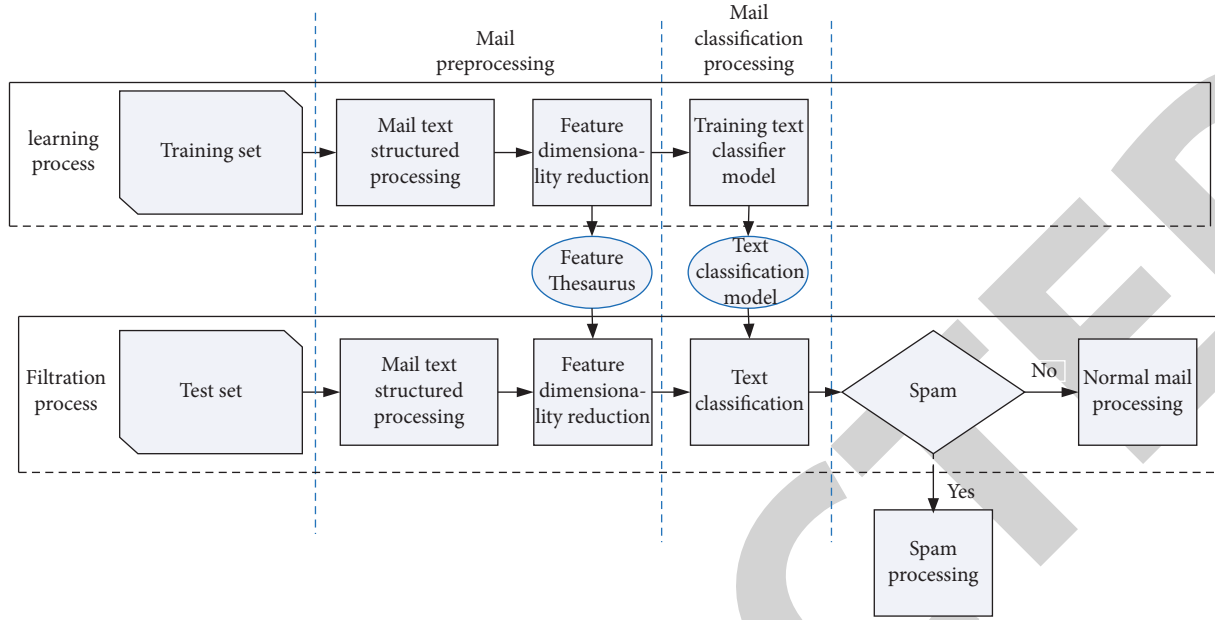


FIGURE 10: Spam classification process.

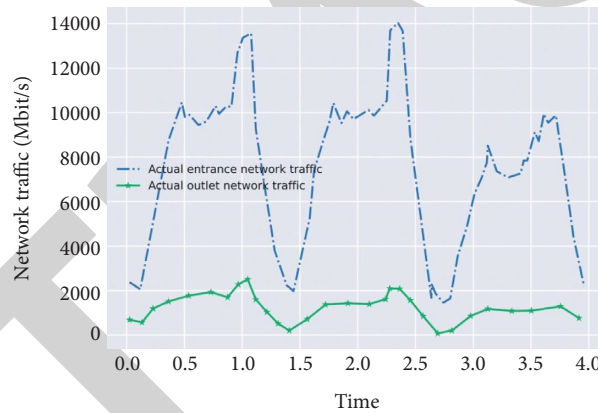


FIGURE 11: Service traffic prediction results based on linear regression.

TABLE 1: Comparison of prediction accuracy of ARIMA and ARIMA + boosting.

Prefecture (city)	Input rate accuracy/%		Output rate accuracy/%	
	ARIMA	ARIMA + Boosting	ARIMA	ARIMA + Boosting
A	72.21	92.37	71.52	97.23
B	70.85	93.5	80.8	98.97
C	87.6	96.43	77.79	89.92
D	81.5	96.19	73.62	94.43

calculate $d(q_j, \mu_2)$ again so that each sample can be assigned to the class with the closest interval. Then, the new center of mass of each class is found once again and the sample points are assigned, and the above process is continued until the center of mass does not change anymore.

3.2. Computer Network Security Management. In the context of gradually expanding the popularity of big data, various important information is stored in computer networks. In

order to effectively guarantee the privacy of users' personal information and enhance the security of data, AI can be introduced into computer networks to strengthen computer security management capabilities. Based on the Naive Bayes algorithm, spam can be filtered. The specific process is shown in Figure 10. The k values of $P(a_j|b_i)$ are calculated, and if $P(a_j|b_i)$ is the maximum of these k values, mail b_i is classified into a_j classes.

Naive Bayes algorithm is a ML method for classifying sample data based on probability statistics, which assumes

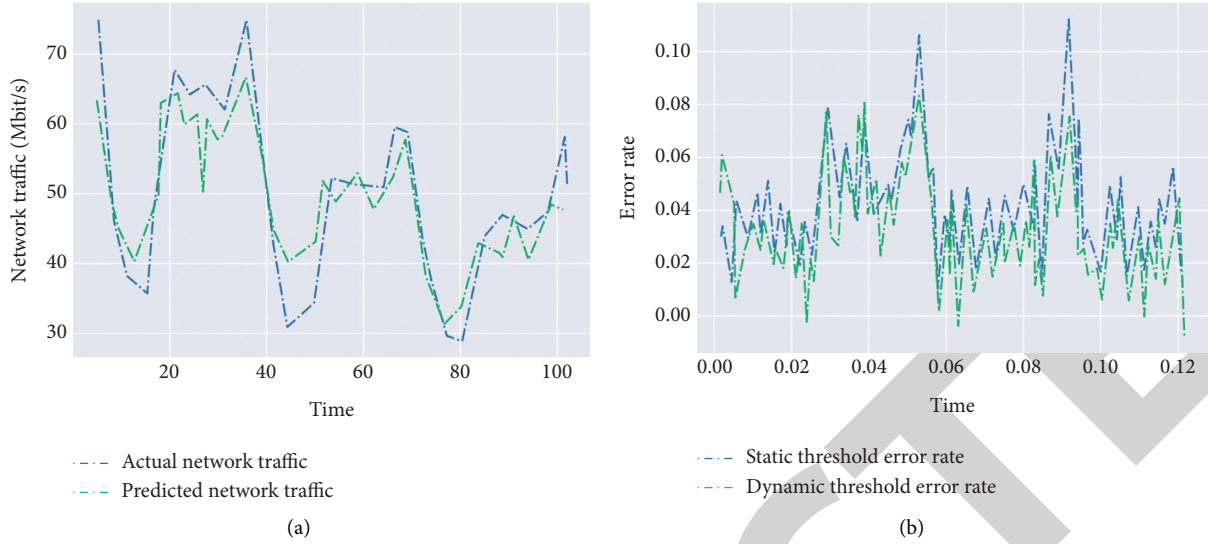


FIGURE 12: Flow forecasting based on ARIMA + boosting + dynamic threshold model. (a) Flow forecast results. (b) Error rate curve.

the prerequisite that the samples are independent of each other. Let the category set be $(a_1, a_2, a_3, \dots, a_n)$ and the mail document be b_j ; then, the probability that the sample b_j belongs to a category a_j is calculated.

In order to improve the computing time efficiency, the traditional Naive Bayes algorithm can be optimized by fusing Naive Bayes algorithm with incremental learning, which improves the spam screening and correct rate. Since spam classification is a real-time updating process and new web languages are emerging all the time, the training set of a priori samples is not comprehensive enough.

4. Case Study

Network performance metrics (i.e., time series) have stability or regularity, and past trends will continue in the future. Based on this core idea, in order to achieve real-time monitoring of each metric, this paper takes into account data characteristics, modeling complexity, prediction accuracy, and application scenarios.

Company A used classical linear regression, ARIMA + Boosting model, and Holt-Winters algorithm in several AI innovation projects and chose dynamic threshold and static threshold methods, respectively, to achieve time series prediction and anomaly alert function for existing network indicators and achieved good application results. The following is a detailed description of the 3 sets of solutions.

Constructing a suitable algorithmic framework to mine the metric change patterns, accurately predicting the network performance metrics through feature learning of historical data, and selecting a suitable threshold setting method, we finally realize the alerting of abnormal events.

4.1. Application of Linear Regression in Performance Metrics Prediction. With the development of services in the direction of diversification and differentiation, network change (cutover) has become a daily operation for operators to cope

with the demand of multiple scenarios such as relay expansion and equipment entry. A company has now developed and launched an AI network unmanned system to solve the problem of time consumption, high risk, and low efficiency of cutover tasks.

In the process of determining the flow anomaly, this program uses the dynamic threshold method of the base 3σ criterion to trigger the alarm. We define the error rate $\Delta = |\text{predicted value} - \text{actual value}| / \text{predicted value} \times 100\%$. By calculating the error rate of the historical flow data, the mean μ and variance σ of the error rate are obtained. If the error rate Δ of the current moment satisfies $|\Delta - \mu| \geq 3\sigma$, the flow is considered to be abnormal at this time and the cutover verification is triggered to fail.

Figure 11 shows the prediction results of a customer service traffic of IDC equipment using linear regression and the abnormal trigger based on the 3σ criterion, and the abnormal traffic is found at the arrow. The method can better fit the trend of indicator changes and can effectively detect anomalies to achieve postcutover healthiness decisions.

4.2. Application of ARIMA in Performance Metrics Prediction.

A company uses Big Data + AI capabilities to perform traffic modeling to help network departments predict network and service traffic and guide network expansion with precision. In this paper, we use the ARIMA algorithm to implement traffic data regression analysis and build the Boosting model to improve the prediction accuracy of time series.

In this paper, the logic of using static thresholds to implement traffic anomaly alerts is to calculate the error rate and issue an alert when the error rate is greater than a set threshold. The error rate $\Delta = |\text{predicted value} - \text{actual value}| / \text{predicted value}$ is set when the error rate is greater than a fixed threshold value to issue an alarm. This alarm method has a major drawback.

The model is trained using the historical data of the past week, and the trend prediction of traffic rate for the next 24 h

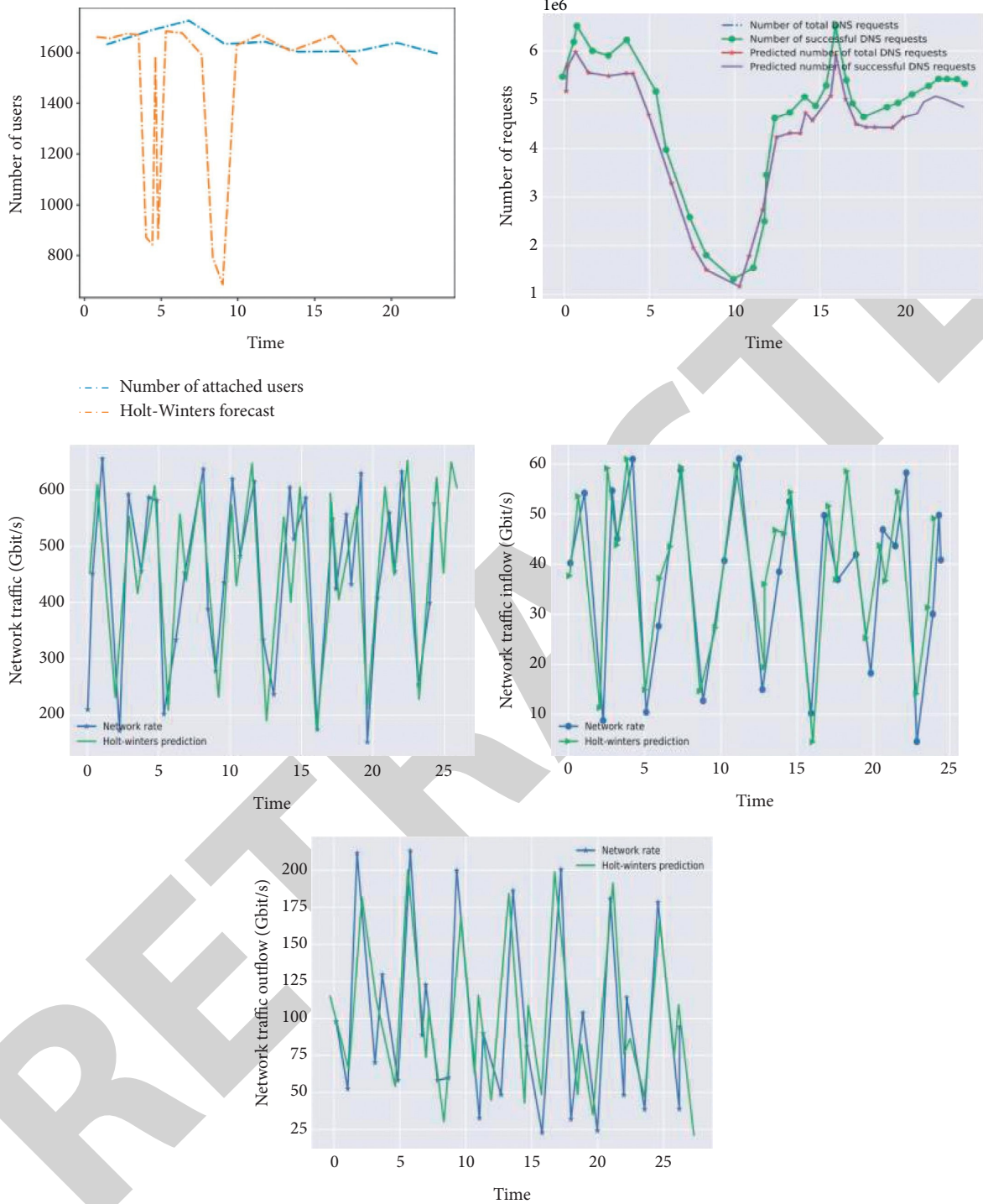


FIGURE 13: Graph of Holt-Winters prediction results across disciplines and multiple indicators.

is performed. The prediction value = $0.5 \times$ ARIMA prediction value + $0.5 \times$ Boosting prediction value. Table 1 compares the accuracy of the ARIMA and ARIMA + Boosting models, and the results show that Boosting greatly optimizes the prediction performance and improves the accuracy by nearly 20%.

To address the above issues, this solution uses a dynamic threshold method to implement anomaly alerts. When training the model using the historical data of the previous week, the value of the 85th percentile (P85) of the data set is calculated statistically, where the 85th percentile is the traffic rate value that falls at the 85% position of the length of the data set by

sorting the traffic data from smallest to largest. Traffic anomalies are determined based on the following: error rate $\Delta = |\text{predicted value} - \text{actual value}|/H \geq \xi$, where $H = (P_{85} + \text{predicted value})/2$ and ξ is the set threshold value.

As shown in Figure 12(a), the ARIMA + Boosting model can achieve accurate prediction for periodically varying flows, but the fit needs to be improved for the detailed part of the random fluctuations of the data. As can be seen from Figure 12(b), the error rate value in the trough region of the prediction curve with the improved dynamic threshold method is smaller than that with the static threshold, which can reduce the false alarm rate in the trough region.

The prediction results of some performance indicators based on the Holt–Winters + static threshold method are shown in Figure 13, and the red part of the graph indicates that the indicator abnormality is detected at that time. From Figure 13, it can be seen that the framework can make accurate predictions for a variety of metrics, helping O&M staff to detect faults in advance.

4.3. Application in Performance Metrics Prediction. Specifically, the system collects historical data on several metrics such as MAN/carrier network/IoT traffic, number of packet network attached users and success rate, number of IoT/fixed-line broadband users, and DNS request volume. The solution uses the Holt–Winters algorithm to take the data of the past week for model training to achieve the data prediction of the future day. To ensure the accuracy and validity of the alarms, the system sets strong alarm rules and actual value and predicted value are greater than the corresponding threshold value. For different indicators, each profession sets different thresholds according to the alarm rules to achieve abnormal warnings.

5. Conclusion

The 5G era and the big data era have brought new challenges to network operations. The traditional network communication technology can no longer meet the actual needs. This paper proposes an artificial intelligence search method based on the K-means algorithm and uses the relative distance between elements to represent the degree of dissimilarity of different types of variables. As an emerging IT technology, artificial intelligence has unique advantages in data extraction and data processing. Compared with traditional measurement methods, artificial intelligence and measurement methods are more effective and flexible and can also adapt to different environments. Network security services have made great contributions to ensuring the safe operation of information infrastructure. It is necessary to actively apply AI technology, analyze its role in promoting network security, establish the concept of network security intelligent operation, and improve the intelligence and automation level of network security services.

Data Availability

The experimental data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares no conflicts of interest regarding this work.

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