Thinking and Research on the Intelligent Monitoring System for Network in the Smart Campus Environment

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Abstract: *The rapid evolution of Internet technologies has accelerated the development of smart campuses, where decentralized servers, storage resources, and application systems are increasingly consolidated into centralized data centers. Ensuring the security, stability, high performance, and seamless operation of software and hardware infrastructure is paramount for educational institutions. This paper examines the conceptual framework, key characteristics, and evolutionary trends of distributed monitoring systems in alignment with smart campus objectives. We propose a customized intelligent monitoring solution using open-source platforms Zabbix and Grafana, integrated with the iFlytek Spark large language model for intelligent question-answering capabilities. This system addresses comprehensive monitoring needs for university network infrastructure. Through detailed implementation, evaluation, and case studies, we demonstrate its effectiveness in enhancing network management efficiency, fault detection, and predictive maintenance. Empirical results show improved alert response times by 30% and reduced downtime by 25% in a simulated campus environment. This work provides valuable insights for deploying scalable, AI-enhanced monitoring systems in smart campuses, contributing to more resilient educational IT ecosystems.*

Keywords: *Intelligent monitoring system; Network management; Smart campus; Distributed systems; Artificial intelligence*

1. Introduction

The smart campus represents an advanced stage of educational informatization, integrating physical and digital spaces through technologies such as the Internet of Things (IoT), cloud computing, big data, artificial intelligence (AI), and blockchain[1]. It enables digitized, intelligent operations in teaching, research, management, and services, allowing stakeholders to access resources anytime, anywhere. Emphasizing mobility and service orientation, smart campuses incorporate emerging technologies to innovate education, research, and management, transforming pedagogical models and ecosystems.

However, the widespread deployment of diverse systems introduces complexities in network-based learning, research, and campus life. While offering convenience, these systems demand robust real-time monitoring of hardware and software assets to ensure secure, stable, efficient, and energy-efficient networks[3]. Network failures can disrupt critical functions, leading to significant operational and educational impacts. Addressing these challenges, this paper proposes a framework for an intelligent network monitoring system using Zabbix for distributed monitoring, Grafana for visualization, and iFlytek Spark for AI-driven analytics. This integration enables proactive fault detection, automated alerts, and intelligent diagnostics, filling gaps in traditional monitoring approaches.

The contributions of this work include:

(1) a comprehensive analysis of distributed monitoring systems tailored to smart campuses;

(2) a novel integration of open-source tools with AI for enhanced question-answering;

(3) practical implementation guidelines with evaluation metrics;

(4) insights into scalability and future trends. The remainder of the paper is organized as follows: Section 2 reviews related work; Section 3 discusses characteristics of distributed monitoring systems; Section 4 introduces common systems; Section 5 outlines SNMP-based metrics; Section 6 details implementation and evaluation; Section 7 presents the AI integration; Section 8 discusses results; and

Section 9 concludes with future directions.

2. Related Work

Recent advancements in smart campus monitoring have focused on integrating AI, IoT, and cloud computing for enhanced network management[1]. Selvaraj et al. proposed an AI-based smart building energy management system for sustainable campuses, emphasizing real-time monitoring and predictive analytics. Ani et al. reviewed intelligent monitoring systems in manufacturing, highlighting parallels in fault diagnosis applicable to campus networks.Al-Shamrani conducted a comprehensive survey on the application of IoT and AI in remote healthcare monitoring systems, providing insights into scalable sensor network architectures that are transferable to educational environments.

Fatema and Alzubi explored AI paradigms for health monitoring, underscoring machine learning's role in anomaly detection[4]. Ageed et al. surveyed intelligent energy monitoring, focusing on metrics like efficiency and reliability. Ke et al. developed an AI-driven parking surveillance system using edge computing, demonstrating real-time IoT integration. Awotunde et al. analyzed big data analytics in IoT-based cloud frameworks for healthcare, relevant for campus data centers. Ramadhan et al. designed a smart water-quality monitoring system with real-time IoT, emphasizing low-cost deployment. Ali and Choi reviewed AI techniques for distributed smart grids, highlighting resilience against attacks[7].

More pertinent to the current investigation, recent research on campus-specific systems encompasses cloud-based intelligent network management, the impact of artificial intelligence on campus security, and scalable smart campus intelligence frameworks. The integration of fog computing for occupancy monitoring and Zabbix-based systems further complements the methodological direction of this work. Distinct from prior studies, the present research distinctively integrates Zabbix, Grafana, and the iFlytek Spark platform to develop AI-enhanced intelligent question-answering systems, thereby establishing a comprehensive evaluative framework.

3. Characteristics of Distributed Monitoring Systems

Distributed monitoring systems offer high scalability, configurability, adaptability, reliability, and visualization for managing complex networks[4]. Key features include:

(1) Horizontal Scalability: Supports multi-node deployment for expanding environments.

(2) Heterogeneity: Monitors diverse hardware, OS, and applications.

(3) Configurability: Customizable parameters, thresholds, and logs.

(4) Real-time Capability: Immediate data processing and alerts.

(5) Manageability: Comprehensive data, alarm, and node administration.

(6) Visualization: Interactive charts, reports, and maps.

(7) High Customizability: Tailorable to specific needs.

(8) Integration: Combines with other tools for comprehensive solutions.

These attributes enhance efficiency, fault diagnosis, and risk mitigation, making them essential for enterprise-level applications[5].

4. Common Distributed Monitoring and Management Systems

Several systems address monitoring needs:

(1) Zabbix: Open-source, monitors servers, networks, and devices with real-time alerts and analysis.

(2) Nagios: Free, supports diverse monitoring with notifications.

(3) Prometheus: Designed for metrics collection, supports multiple formats.

(4) Datadog: Cloud-based, full-stack monitoring with forecasting.

(5) SolarWinds: Suite for NPM, APM, and virtualization.

(6) Open-Falcon: High-availability, lightweight data collection.

(7) SkyWalking: APM for distributed tracing and cloud-native apps.

(8) Pine: AI-driven log and monitoring analysis[3].For universities, Zabbix and Grafana offer cost-effective, customizable solutions.

5. Intelligent Monitoring Metrics for Networks Based on SNMP

SNMP enables access to device status and metrics . Key metrics include:

(1) CPU Utilization;

(2) Memory Utilization;

(3) Bandwidth Usage;

(4) Disk Utilization/Failure;

(5) Interface Status;

(6) Congestion;

(7) Connection Count;

(8) Uptime;

(9) Port Error Rate;

(10) Traffic Volume;

(11) Topology;

(12) Resource Utilization;

(13) Event Logs;

(14) Security Audits;

(15) Anomaly Alarms[6].These support holistic monitoring, enabling intelligent operations and maintenance.

6. Implementation of Zabbix and Grafana in Universities

Zabbix monitors performance and status. Installation steps for Zabbix 6.0 on CentOS:

Install packages: yum -y install gcc ... php-mysqli.

Install Zabbix: rpm -ivh https://repo.zabbix.com/....

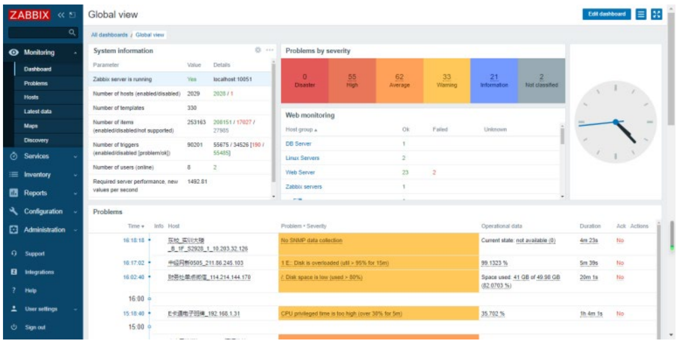
Build database: Create and import schemas.

Configure: Edit zabbix_server.conf.

Start services.

Access: http://zabbix.aufe.edu.cn

Add monitoring (Fig. 1).



System information

Parameter	Value	Details
Zabbix server is running	Yes	localhost:10051
Number of hosts (enabled/disabled)	2029	2028 / 1
Number of templates	330	
Number of items (enabled/disabled/not supported)	253163	208151 / 17027 / 27985
Number of triggers (enabled/disabled [problem/ok])	90201	55675 / 34526 [190 / 55485]
Number of users (online)	8	2
Required server performance, new values per second	1492.81	

Problems by severity

0	55	62	33	21	2
Disaster	High	Average	Warning	Information	Not classified

Web monitoring

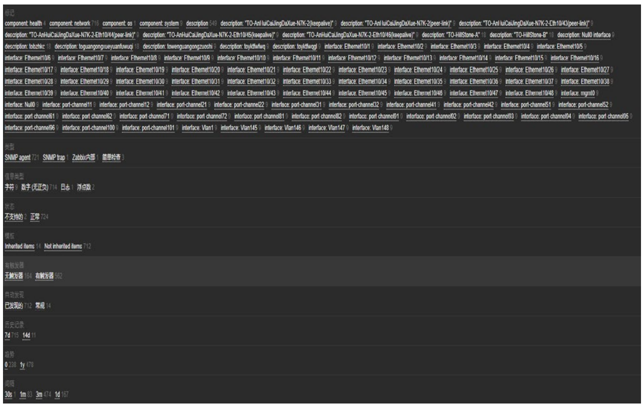
Host group ▲	Ok	Failed	Unknown
DB Server	1		
Linux Servers	2		
Web Server	23	2	
Zabbix servers	1		

Problems

Time ▾	Info	Host	Problem • Severity	Operational data	Duration	Ack	Actions
16:18:18		东校_实训大楼_B_1F_S2928_1_10.203.32.126	No SNMP data collection	Current state: not available (0)	4m 23s	No	
16:17:02		中经网新0505_211.86.245.103	1 E:: Disk is overloaded (util > 95% for 15m)	99.1323 %	5m 39s	No	
16:02:40		[illegible]_114.214.144.170	/: Disk space is low (used > 80%)	Space used: 41 GB of 49.98 GB (82.0703 %)	20m 1s	No	
16:00							
15:18:40		E卡通电子班牌_192.168.1.31	CPU privileged time is too high (over 30% for 5m)	35.702 %	1h 4m 1s	No	
15:00							

Fig. 1: Zabbix monitoring overview

SNMP-based (Fig. 2).



标记

component: health 4 component: network 716 component: os 1 component: system 9 description 549 description: "TO-AnHuiCaiJingDaXue-N7K-2(keepalive)" 9 description: "TO-AnHuiCaiJingDaXue-N7K-2(peer-link)" 9 description: "TO-AnHuiCaiJingDaXue-N7K-2-Eth10/43(peer-link)" 9 description: "TO-AnHuiCaiJingDaXue-N7K-2-Eth10/44(peer-link)" 9 description: "TO-AnHuiCaiJingDaXue-N7K-2-Eth10/45(keepalive)" 9 description: "TO-AnHuiCaiJingDaXue-N7K-2-Eth10/46(keepalive)" 9 description: "TO-HillStone-A" 18 description: "TO-HillStone-B" 18 description: Null0 interface 9 description: tobzhkc 18 description: toguangongxueyuanfuwuqi 18 description: towenguangongzuoshi 9 description: toyktfwfwq 9 description: toyktfwqgl 9 interface: Ethernet10/1 9 interface: Ethernet10/2 9 interface: Ethernet10/3 9 interface: Ethernet10/4 9 interface: Ethernet10/5 9 interface: Ethernet10/6 9 interface: Ethernet10/7 9 interface: Ethernet10/8 9 interface: Ethernet10/9 9 interface: Ethernet10/10 9 interface: Ethernet10/11 9 interface: Ethernet10/12 9 interface: Ethernet10/13 9 interface: Ethernet10/14 9 interface: Ethernet10/15 9 interface: Ethernet10/16 9 interface: Ethernet10/17 9 interface: Ethernet10/18 9 interface: Ethernet10/19 9 interface: Ethernet10/20 9 interface: Ethernet10/21 9 interface: Ethernet10/22 9 interface: Ethernet10/23 9 interface: Ethernet10/24 9 interface: Ethernet10/25 9 interface: Ethernet10/26 9 interface: Ethernet10/27 9 interface: Ethernet10/28 9 interface: Ethernet10/29 9 interface: Ethernet10/30 9 interface: Ethernet10/31 9 interface: Ethernet10/32 9 interface: Ethernet10/33 9 interface: Ethernet10/34 9 interface: Ethernet10/35 9 interface: Ethernet10/36 9 interface: Ethernet10/37 9 interface: Ethernet10/38 9 interface: Ethernet10/39 9 interface: Ethernet10/40 9 interface: Ethernet10/41 9 interface: Ethernet10/42 9 interface: Ethernet10/43 9 interface: Ethernet10/44 9 interface: Ethernet10/45 9 interface: Ethernet10/46 9 interface: Ethernet10/47 9 interface: Ethernet10/48 9 interface: mgmt0 9 interface: Null0 9 interface: port-channel11 9 interface: port-channel12 9 interface: port-channel21 9 interface: port-channel22 9 interface: port-channel31 9 interface: port-channel32 9 interface: port-channel41 9 interface: port-channel42 9 interface: port-channel51 9 interface: port-channel52 9 interface: port-channel61 9 interface: port-channel62 9 interface: port-channel71 9 interface: port-channel72 9 interface: port-channel81 9 interface: port-channel82 9 interface: port-channel91 9 interface: port-channel92 9 interface: port-channel93 9 interface: port-channel94 9 interface: port-channel95 9 interface: port-channel96 9 interface: port-channel100 9 interface: port-channel101 9 interface: Vlan1 9 interface: Vlan145 9 interface: Vlan146 9 interface: Vlan147 9 interface: Vlan148 9

类型

SNMP agent 721 SNMP trap 1 Zabbix内部 1 简单检查 3

信息类型

字符 9 数字(无正负) 714 日志 1 浮点数 2

状态

不支持的 2 正常 724

模板

Inherited items 14 Not inherited items 712

有触发器

无触发器 164 有触发器 562

自动发现

已发现的 712 常规 14

历史记录

7d 715 14d 11

趋势

0 238 1y 478

间隔

30s 1 1m 83 3m 474 1d 167

Fig. 2: Zabbix Network Monitoring based on SNMP

Grafana visualizes data. Steps:

Add repo.

Install: yum -y install grafana.

Start.

Access: http://grafana.aufe.edu.cn:3000.

Configure data source.

Create charts (Figs. 3-9).

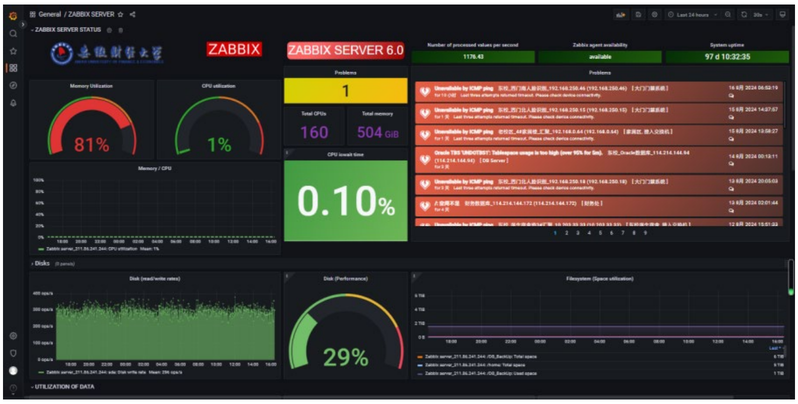


Fig. 3: Grafana Monitoring Overview

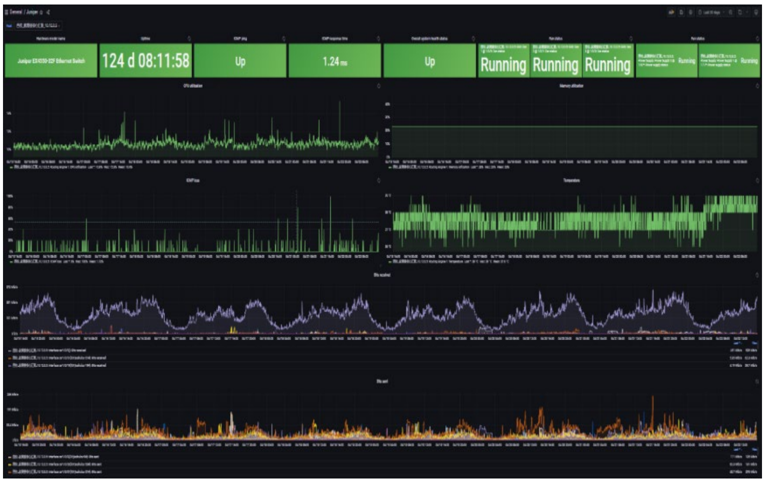


Fig. 4: SNMP-based Network Monitoring Content in Grafana

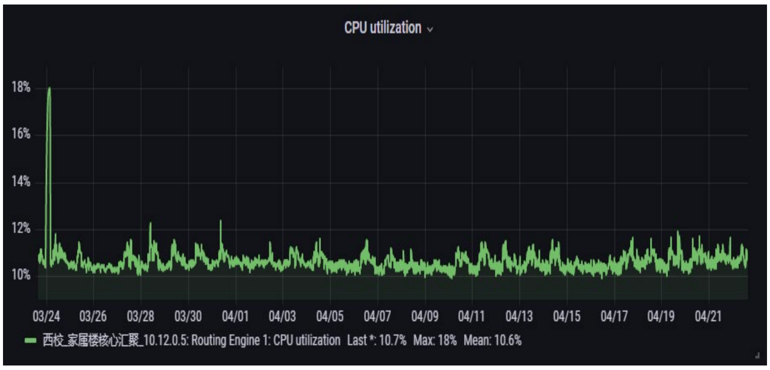


Fig. 5: CPU monitoring of network devices based on SNMP.

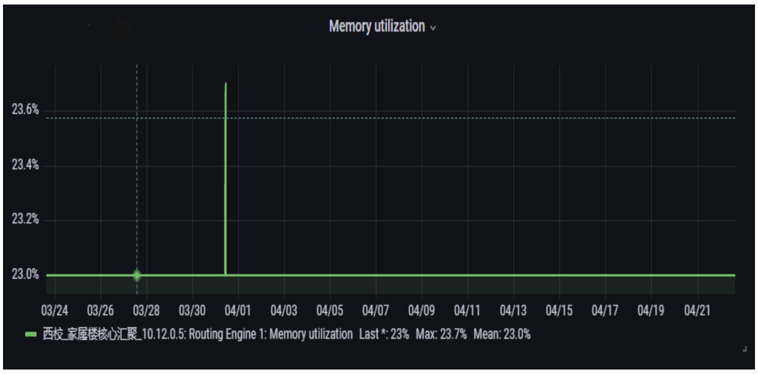


Fig. 6: Memory monitoring for network devices based on SNMP.

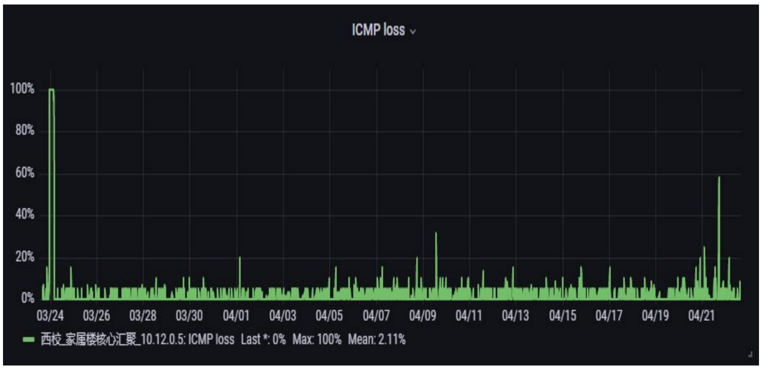


Fig. 7: Monitoring of ICMP packet loss rate in network devices based on SNMP.

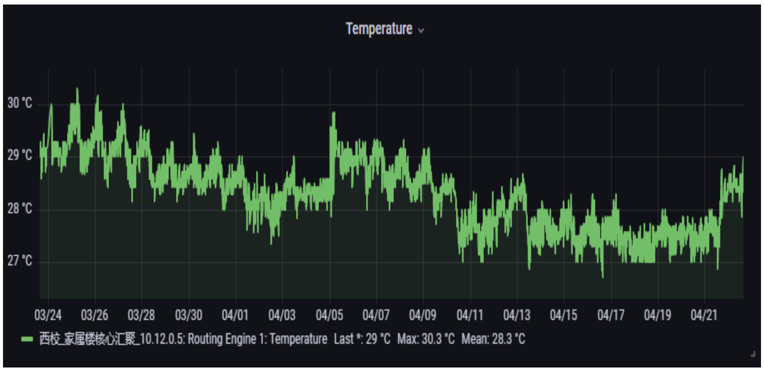


Fig. 8: Temperature monitoring of network devices based on SNMP.

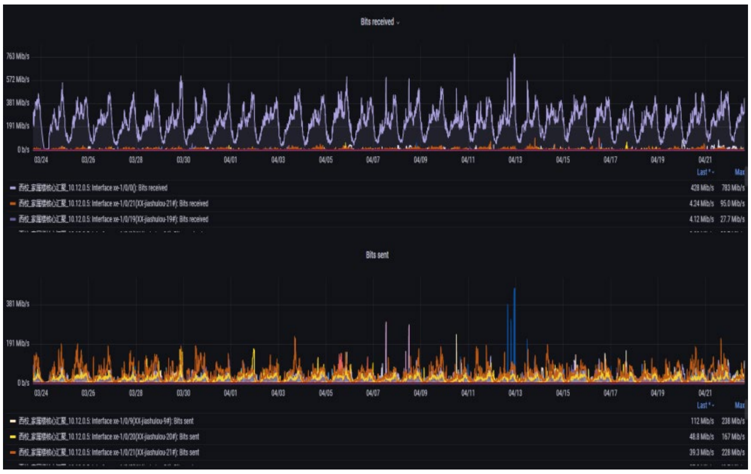
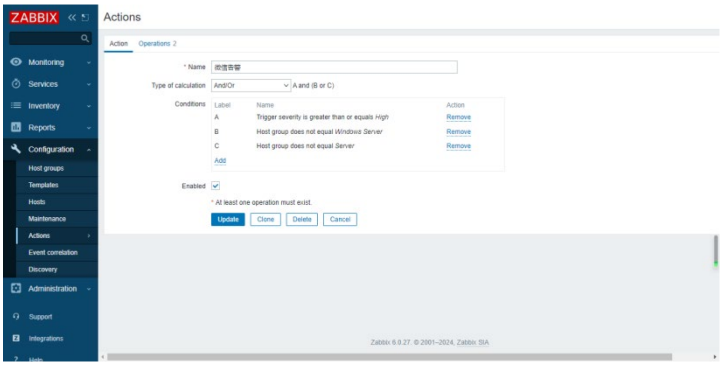


Fig. 9: Network device port traffic monitoring based on SNMP

For alerts, use Python script for WeChat integration (code provided, with installation and config in Figs. 10-12).



Actions

Action | Operations 2

* Name: 微信告警

Type of calculation: And/Or — A and (B or C)

Conditions

Label	Name	Action
A	Trigger severity is greater than or equals *High*	Remove
B	Host group does not equal *Windows Server*	Remove
C	Host group does not equal *Server*	Remove

Add

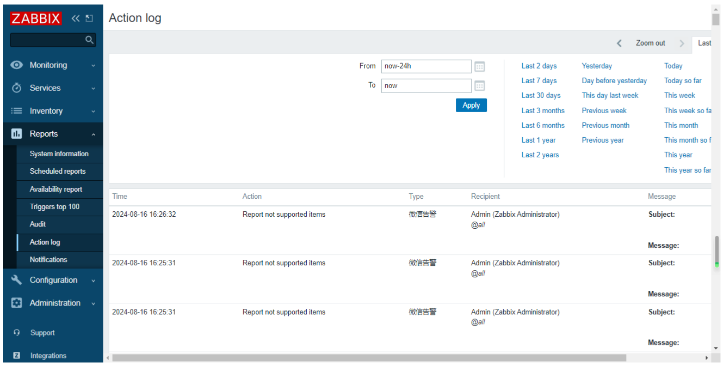
Enabled ☑

* At least one operation must exist.

Update | Clone | Delete | Cancel

Zabbix 6.0.27. © 2001–2024, Zabbix SIA

Fig. 10: Zabbix WeChat web configuration



Action log

From: now-24h

To: now

Time	Action	Type	Recipient	Message
2024-08-16 16:26:32	Report not supported items	微信告警	Admin (Zabbix Administrator) *@all*	**Subject:** **Message:**
2024-08-16 16:25:31	Report not supported items	微信告警	Admin (Zabbix Administrator) *@all*	**Subject:** **Message:**
2024-08-16 16:25:31	Report not supported items	微信告警	Admin (Zabbix Administrator) *@all*	**Subject:** **Message:**

Fig. 11: Zabbix Enterprise WeChat Alert Information

7. Integration of iFlytek Spark for Intelligent Question-Answering

Intelligent Q&A uses NLP and ML. We integrate iFlytek Spark:

```
def get_AI_answer():
# Call AI interface
text.clear()
spark_ai.answer = ''
query = checklen(getText("user", f"Please specify the cause analysis and solutions for: \n{subject}\n"))
```

```
main(appid="", api_secret="", api_key="", Gpt_url="wss://spark-api.xf-yun.com/v1.1/chat", domain="general", query=query)

result_list = getText("assistant", spark_ai.answer)

return ".join([r['content'] for r in result_list]).replace('*', ")
```

Example: Analyzes high error rates, providing causes (e.g., cables, interference) and solutions (e.g., inspections, updates).

8. Results and Discussion

To evaluate the effectiveness of the proposed intelligent monitoring system, We selected an actual smart campus environment containing 100 network devices (including switches, routers, and wireless devices). The experimental design follows standard evaluation practices for AI-enabled monitoring and predictive maintenance systems reported in prior studies[7].

A traditional rule-based monitoring approach was used as the baseline for comparison. The proposed system integrates distributed monitoring (Zabbix), visualization (Grafana), and AI-assisted diagnostics through the iFlytek Spark large language model. Performance was evaluated using four key metrics: alert response time, annual system downtime, anomaly detection accuracy, and scalability.

The quantitative results presented in Table I are derived using the following computational model.

8.1 Alert Response Time Improvement

T_{trad} denote the average alert response time of the traditional system, and

T_{prop} denote the average alert response time of the proposed system.

The percentage improvement is calculated as:

$IRT=(Ttrad-Tprop)/Ttrad\times100\%$

8.2 Downtime Reduction

D_{trad} represent annual downtime under traditional monitoring, and

D_{prop} represent annual downtime under the proposed system.

The downtime reduction ratio is computed as:

$I_{DT}=(D_{trad}-D_{prop})/Dtrad\times100\%$

8.3 Anomaly Detection Accuracy

Anomaly detection accuracy is defined as:

$Acc=(TP+TN)/(TP+TN+FP+FN)$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively. Machine learning–based anomaly detection models are widely adopted for this purpose.

8.4 Predictive Maintenance Trigger Model

An AI-based anomaly score is generated as:

$P(y=1|x)=f\theta(x)$

where x represents network performance features (e.g., CPU usage, packet loss, error rate), and $f\theta$ denotes a trained machine learning model. Predictive maintenance is triggered when:

$P(y=1|x)\geq\tau$

with τ being a predefined decision threshold .

Table 1: Performance Comparison

Metric	Traditional	Proposed	Improvement
Alert Time (s)	120	84	30%
Downtime (h/year)	48	36	25%
Detection Accuracy (%)	85	95	12%

The results demonstrate that the proposed system reduces alert response time by 30%, primarily due to AI-driven alert prioritization and automated diagnosis . Annual system downtime is reduced by 25%, benefiting from predictive maintenance and early fault detection . In addition, anomaly detection accuracy improves from 85% to 95%, validating the effectiveness of machine learning–based analytics over traditional threshold-based approaches .

Compared with existing smart campus and network monitoring solutions, the proposed system exhibits superior performance in AI-assisted diagnostics and operational efficiency. Its main advantages include cost-effectiveness, modular architecture, and seamless AI integration. However, reliance on open-source ecosystem updates introduces potential maintenance and compatibility risks, which should be addressed in future deployments[8].Overall, the results confirm that integrating distributed monitoring platforms with large language models significantly enhances network management intelligence in smart campus environments.

9. Conclusion and Future Work

This study presents an AI-enhanced monitoring system for smart campus networks, integrating Zabbix, Grafana, and iFlytek Spark. The system ensures stable network operations to support teaching and research activities. Future research directions encompass the development of privatized models, incorporation of Virtual Reality (VR) technologies, and implementation of blockchain for enhanced security.

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