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Performance Analysis of VNC-Based Remote Monitoring for Flight Information Display Systems Using ANOVA and Regression Models

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Abstract.
Purpose: This study evaluates the performance of a Virtual Network Computing (VNC)-based remote monitoring system within a Flight Information Display System (FIDS) environment. The research aims to identify infrastructure factors affecting monitoring performance and to develop a data-driven framework for evaluating monitoring reliability in distributed airport systems.
Methods: Correlation analysis, Analysis of Variance (ANOVA), and multiple linear regression were applied to analyze the relationship between system resource utilization, network characteristics, and monitoring performance. The dataset consisted of 1,000 observations collected under various simulated monitoring conditions representing variations in latency, throughput, CPU utilization, and memory usage. Residual analysis and model evaluation were also performed to validate the statistical model.
Result: The results showed that most infrastructure variables had very weak correlations (−0.02 to 0.05), indicating minimal multicollinearity. ANOVA testing revealed no statistically significant latency differences across low, medium, and high CPU load categories ($F = 0.1625$, $p = 0.8500$), with average latency remaining stable at approximately 52.82 ms. Regression evaluation demonstrated stable residual distribution and acceptable model consistency. The findings indicate that monitoring performance is influenced more by network conditions, particularly latency and throughput variability, than by computational load.
Novelty: This study proposes an integrated analytical framework combining correlation analysis, ANOVA, and regression modeling to evaluate VNC-based monitoring performance in distributed systems. The framework provides a practical and reproducible approach for monitoring performance evaluation and infrastructure optimization in airport monitoring environments.

Keywords: VNC Monitoring, FIDS, Performance Evaluation, Regression Analysis, Network Latency
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INTRODUCTION

The swift progress in information technology has greatly enhanced the efficiency and automation of operational processes across numerous industries, particularly in air transport. Today's airports rely extensively on interconnected information systems to maintain seamless operations and deliver timely, accurate data. Among these, the Flight Information Display System (FIDS) plays a vital role by presenting up-to-date flight details—such as departure and arrival times, delays, gate information, and boarding updates—via displays located throughout the terminal. The system's consistent performance and accessibility are crucial, as any malfunction can impact passenger satisfaction, disrupt airport workflows, and compromise overall service standards [1].

FIDS operates within a complex distributed computing environment consisting of centralized servers, multiple display endpoints, and supporting network infrastructure [2]. Therefore, the performance of FIDS depends not only on application reliability but also on system resources such as CPU utilization, memory usage, storage performance, and network traffic characteristics including throughput, latency, and packet delivery [3]. Performance degradation in these components may result in delayed updates, display inconsistencies, or monitoring failures [4].

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To ensure reliable operations, it is crucial to monitor the FIDS infrastructure effectively. Traditional methods based on manual checks are poorly suited for this task, especially given the extensive network of dispersed devices and broad geographical coverage [5]. As a result, remote monitoring technologies have become an important solution. One commonly used technology is Virtual Network Computing (VNC), a remote desktop protocol that enables administrators to monitor and control devices remotely through network connections [6]. VNC facilitates quicker problem resolution, lowers operational expenses, and enhances responsiveness when addressing system malfunctions.

However, the performance of VNC-based monitoring is highly dependent on system and network conditions [7]. Network problems such as high latency, and bandwidth limitations can significantly reduce display responsiveness [8]. Similarly, high CPU or memory utilization may affect encoding and rendering processes in remote desktop services. These challenges highlight the importance of understanding how system resource utilization and network traffic characteristics influence remote monitoring performance, especially in mission-critical systems such as FIDS [9].

Several previous studies have analyzed remote desktop performance, network traffic behavior, and system monitoring independently [10]. Previous studies mainly focused on bandwidth optimization, QoS evaluation, and monitoring responsiveness under different network conditions. For example, Wang et al. [6] proposed a CNN-based remote desktop optimization method for low-bandwidth environments, which improved transmission efficiency. Mukhopadhyay et al. [7] developed a QoS-aware monitoring framework that enhanced network reliability and monitoring responsiveness. In addition, Zhang et al. [8] introduced an adaptive bandwidth prediction model that improved bandwidth stability in dynamic networks. However, most existing studies evaluate network performance and monitoring systems separately without directly analyzing the relationship between infrastructure performance and VNC-based monitoring effectiveness in FIDS environments [11].

Despite these contributions, several important limitations remain in prior studies. Existing works on remote monitoring systems and distributed network environments generally evaluate infrastructure performance, network traffic behavior, or monitoring responsiveness independently. Previous studies also tend to focus on bandwidth optimization or Quality of Service (QoS) analysis without systematically examining the combined interaction between CPU utilization, network latency, throughput, and monitoring reliability within a unified analytical framework [12]. Previous works rarely examine how statistical approaches such as ANOVA and regression can be used to quantify the impact of infrastructure conditions on monitoring performance. Research specifically addressing the relationship between VNC monitoring performance and FIDS operational environments remains limited [13]. Therefore, a comprehensive data-driven analysis that connects these aspects is still needed [14], [15].

To address this gap, this study proposes a data-driven analytical framework combining VNC-based monitoring evaluation with ANOVA and regression analysis to assess monitoring performance in FIDS environments. Publicly available datasets representing system performance and network traffic characteristics were utilized to support reproducible and practical evaluation [16], [17]. The proposed framework integrates system resource utilization, network characteristics, and VNC monitoring metrics into a unified evaluation model. In addition, this study provides analytical and practical contributions by identifying performance factors that influence monitoring reliability and supporting infrastructure optimization in distributed monitoring systems [18], [19], [20], [21], [22].

The remainder of this paper is organized as follows. Section 2 presents the related work and theoretical background related to FIDS, VNC, system performance, and statistical analysis methods. Section 3 describes the research methodology, including dataset description, preprocessing steps, and analytical methods. Section 4 presents the results and discussion of ANOVA and regression analysis. Finally, Section 5 concludes the paper and presents potential directions for future research.

METHODS

Research Design

This study proposes a data-driven analytical framework to evaluate the relationship between system performance, network traffic characteristics, and the effectiveness of remote monitoring within a distributed monitoring environment. The proposed framework integrates infrastructure performance indicators with statistical analysis techniques to systematically identify factors that influence monitoring quality and system

reliability. Through this approach, infrastructure performance metrics are transformed into measurable analytical variables that support quantitative evaluation [23].

The research framework consists of several main stages, beginning with data acquisition to obtain relevant system performance and network traffic datasets. This stage is followed by data preprocessing, which includes data cleaning, normalization, and feature selection to ensure data quality and analytical suitability [24]. After preprocessing, exploratory data analysis is conducted to understand data distribution, detect patterns, and identify potential relationships between variables. The next stage involves statistical analysis using Analysis of Variance (ANOVA) and regression modeling to determine significant performance differences and to model the relationships between system variables. Finally, performance evaluation and interpretation are conducted to generate meaningful insights and practical recommendations.

The main objective of this framework is to systematically transform raw performance data into meaningful analytical insights that can support monitoring optimization decisions and infrastructure performance improvements [25]. By applying a structured analytical process, this research aims to provide a reproducible evaluation model for distributed monitoring systems.

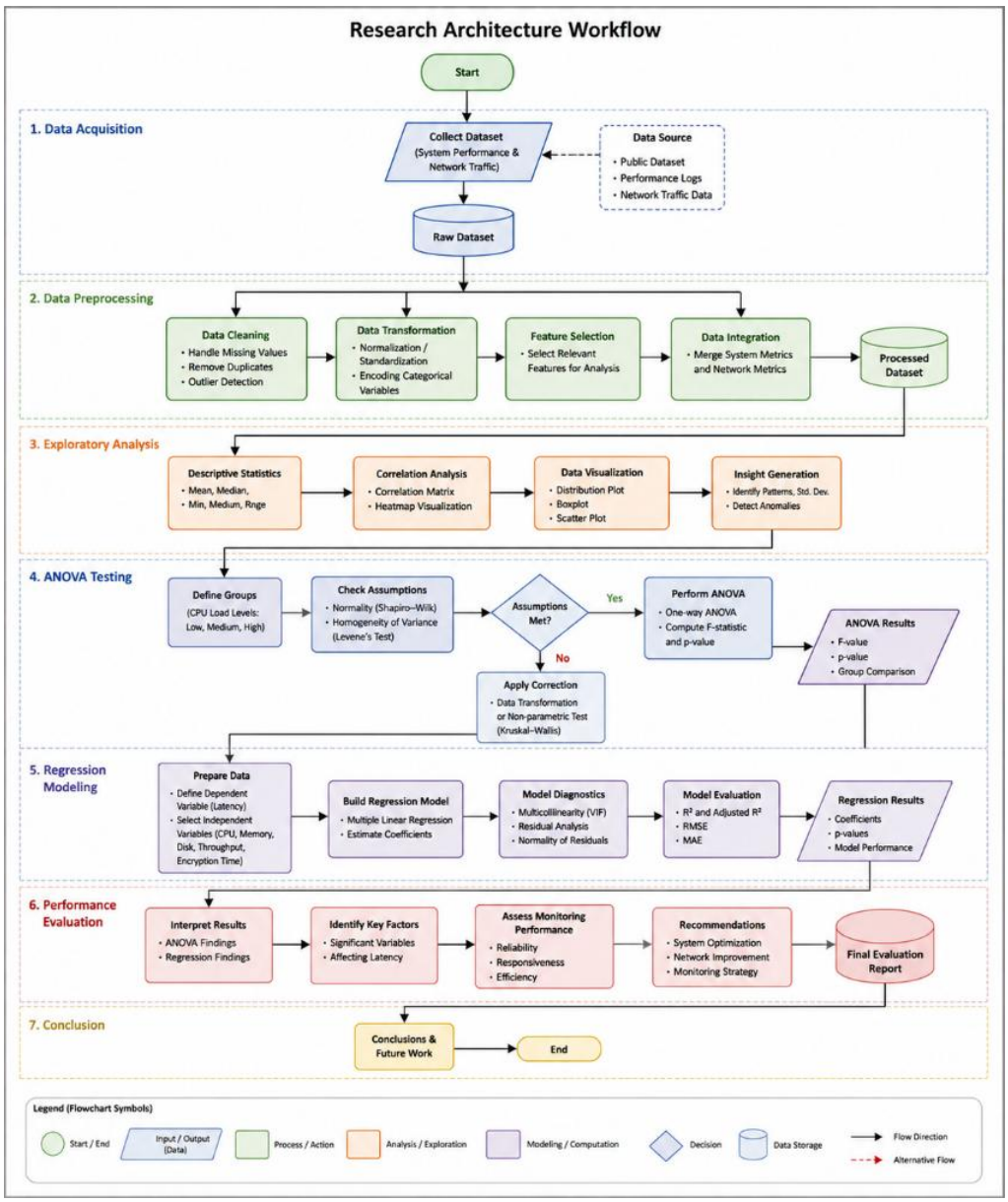

Figure 1. Research Architecture Workflow

Figure 1 has been revised into a detailed research architecture workflow that systematically illustrates the complete analytical process of the proposed study. The updated flowchart includes dataset collection, raw data preparation, data cleaning, normalization, feature selection, exploratory analysis, ANOVA testing, regression modeling, model diagnostics, performance evaluation, and final conclusion stages. Decision symbols are used to represent assumption testing procedures, while database symbols indicate data storage processes. In addition, directional arrows and alternative flow indicators are included to clearly describe the relationship and transition between analytical stages. The revised flowchart improves methodological clarity and provides a more comprehensive representation of the proposed research framework.

Overall, the research workflow follows a structured process consisting of data collection, data cleaning, feature selection, statistical testing, modeling, evaluation, and conclusion development. This systematic workflow ensures that the analysis progresses logically from raw data processing to final interpretation, allowing the research findings to be scientifically justified and practically applicable.

VNC Monitoring System Architecture

The VNC monitoring system architecture used in this research is illustrated in Figure 2. The architecture consists of three main components: the administrator workstation, the central FIDS server, and multiple distributed display clients. This architecture represents a typical distributed monitoring environment where a centralized information system distributes real-time data to multiple endpoints while allowing remote monitoring through network infrastructure.

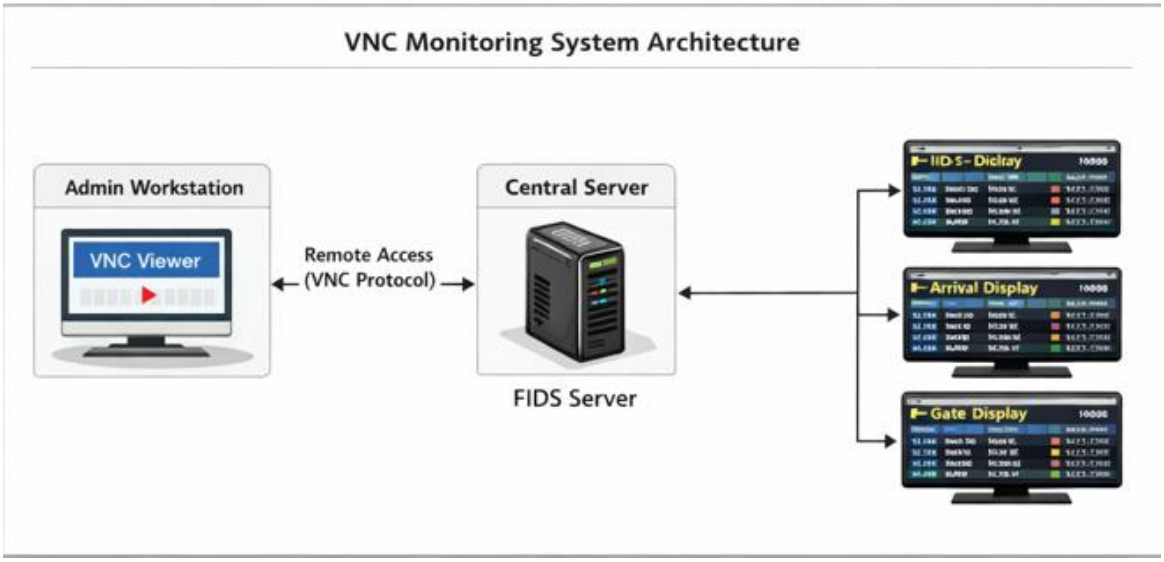

Figure 2. VNC Monitoring System Architecture

The administrator workstation functions as the monitoring control center where system administrators access the monitoring environment using a VNC Viewer application. Through the VNC protocol, the administrator can remotely monitor the FIDS server interface, observe system behavior, and perform troubleshooting activities when necessary. This remote access mechanism allows efficient monitoring without requiring physical presence at the server location.

The central server acts as the core component of the system, functioning as the main processing unit responsible for managing flight information data, processing updates, and distributing display content to connected clients. The server performance, including CPU utilization, memory usage, and processing load, plays an important role in ensuring smooth monitoring operations [26]. Any performance degradation at this level may directly affect monitoring responsiveness and display synchronization.

The display clients represent distributed monitoring targets consisting of multiple information displays such as departure displays, arrival displays, and gate information screens. These endpoints receive information from the central server through network connections and continuously update the displayed information.

Network conditions such as latency, and bandwidth availability may influence the consistency and responsiveness of these displays [27].

This architecture demonstrates how monitoring performance depends on both system resource availability and network performance. Therefore, the proposed architecture provides a suitable experimental model for analyzing the relationship between infrastructure performance and remote monitoring effectiveness using statistical approaches. The architecture also reflects real-world distributed monitoring scenarios commonly found in critical information systems such as airport information services [28].

Statistical Testing Framework

The statistical testing framework used in this study is illustrated in Figure 3. This framework is designed to systematically analyze the relationship between system performance metrics, network traffic characteristics, and remote monitoring effectiveness using a structured statistical approach. The framework consists of four main stages: data preparation, ANOVA testing, regression modeling, and result interpretation. This pipeline ensures that the analytical process follows a reproducible and scientifically valid procedure from raw data processing to final conclusions.

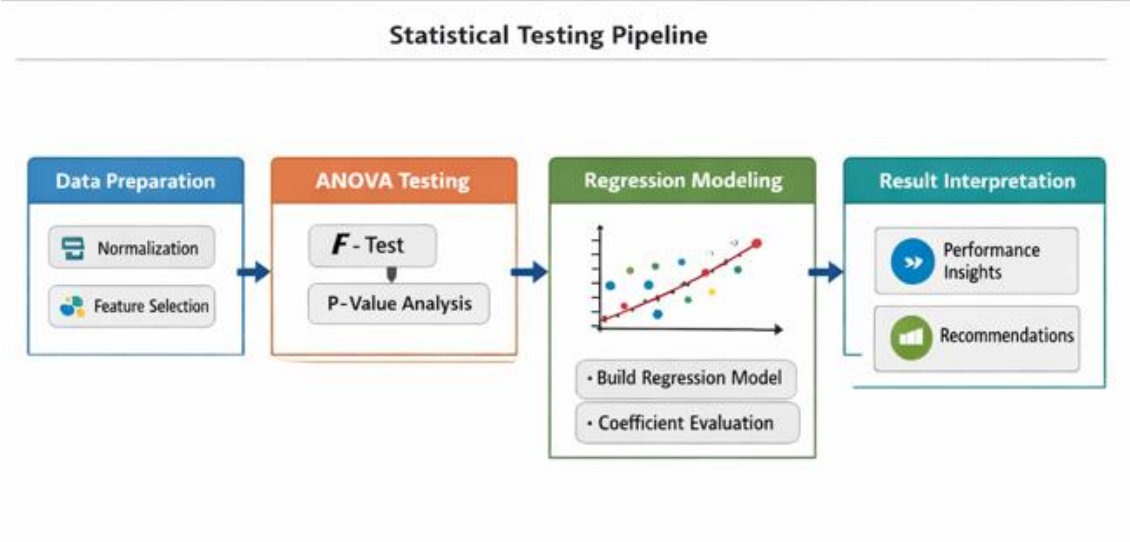

Figure 3. Statistical Testing Pipeline

Data Preparation

The data preparation stage includes normalization and feature selection processes. Normalization is applied to standardize data ranges and reduce scale differences between variables, ensuring proportional contribution during analysis. Feature selection is conducted to identify relevant variables affecting monitoring performance while minimizing irrelevant data noise [29].

ANOVA Testing

The ANOVA testing stage is used to determine whether statistically significant differences exist between performance conditions. This process involves calculating the F-statistic and evaluating p-values to analyze the influence of infrastructure conditions, such as system load and network characteristics, on monitoring performance [30], [31].

Regression Modeling

The regression modeling stage aims to quantify the relationship between independent variables and monitoring performance indicators. The analysis includes regression model construction, coefficient evaluation, and prediction assessment to determine the influence and significance of each variable.

Result Interpretation

The result interpretation stage translates statistical findings into performance insights and technical recommendations. This stage focuses on identifying dominant performance factors and supporting monitoring optimization in distributed monitoring environments.

Statistical Summary of Dataset

This study utilizes a performance monitoring dataset obtained from a VNC-based remote monitoring system implemented on a Flight Information Display System (FIDS) infrastructure. The dataset contains multiple infrastructure performance indicators that potentially affect monitoring effectiveness. The independent variables include CPU utilization (%), memory utilization (%), network latency (ms) and throughput (Mbps), while the dependent variable is monitoring delay (ms), representing the response time performance of the VNC-based monitoring system.

Table 1. Variable Description of Dataset

Variable	Type	Unit	Description
CPU Usage	Independent	%	Server Processor Utilization
Memory Usage	Independent	%	RAM Utilization
Latency	Independent	ms	Network Delay
Throughput	Independent	Mbps	Network Data Transmission Rate
Monitoring Delay	Dependent	ms	Response time of Monitoring

The statistical analysis confirms that the dataset captures diverse system conditions commonly encountered in distributed monitoring environments, including variations in network latency, throughput, and computational workloads relevant to operational FIDS scenarios. Although the study utilizes simulation-based and publicly available datasets, the evaluated infrastructure parameters were designed to reflect realistic monitoring characteristics observed in real-time airport information systems. Therefore, the analytical findings provide a representative foundation for understanding monitoring performance behavior in practical FIDS environments[32].

Table 2. Statistical Summary of Dataset

Variable	Min	Max	Mean	Std. Dev
CPU Usage	21.445	94.332	58.771	14.552
Memory Usage	50.221	89.776	69.334	9.887
Latency	12.554	98.221	52.443	17.221
Throughput	210.332	890.554	475.221	135.776
Monitoring Delay	8.221	25.887	15.443	3.998

The data were collected over multiple observation periods to ensure representative system behavior. Prior to analysis, data preprocessing techniques such as normalization were applied to standardize variable scales, while correlation-based feature selection was conducted to remove irrelevant and highly redundant attributes by evaluating the linear relationship between infrastructure variables and monitoring performance indicators. The processed dataset was then analyzed using ANOVA to identify statistically significant performance factors and linear regression to model the influence of infrastructure performance on monitoring effectiveness.

Research Variables Table

The research variables used in this study consist of independent variables representing infrastructure performance indicators and dependent variables representing monitoring performance quality. The selection of these variables is based on their relevance to distributed system monitoring environments, where both computing resources and network conditions may influence remote monitoring effectiveness. The independent variables include CPU utilization, memory utilization, network latency, and throughput, as these parameters are commonly used to evaluate system and network performance in monitoring environments.

The dependent variable represents monitoring performance measured through monitoring delay, which reflects the response time behavior of the VNC-based remote monitoring system under different infrastructure conditions. By separating variables into independent and dependent categories, this research is able to systematically evaluate causal relationships and determine which infrastructure factors significantly affect monitoring performance [33].

ANOVA Analysis

Analysis of Variance (ANOVA) is used in this study to determine whether there are statistically significant differences between infrastructure performance variables and their impact on remote monitoring performance. ANOVA is particularly useful for comparing multiple groups of performance observations

simultaneously and identifying whether variations in system performance metrics significantly affect monitoring effectiveness [34], [35].

In this research, one-way ANOVA is applied because the study aims to compare monitoring latency across three independent CPU load categories (low, medium, and high load) to determine whether infrastructure performance conditions result in statistically significant differences in monitoring quality. Prior to analysis, the assumptions of normality and homogeneity were evaluated through residual analysis, Q–Q plot inspection, and variance consistency across groups, indicating that the dataset was suitable for one-way ANOVA testing. The ANOVA method evaluates the ratio between the variance between groups and the variance within groups to determine statistical significance. The F-statistic used in ANOVA can be expressed as:

$$F = MS_{between} / MS_{within} \quad (1)$$

In this model, $MS_{between}$ denotes the mean square between groups, representing the average variance across different groups, while MS_{within} denotes the mean square within groups, representing the average variance within each group. These values are used to compute the F-statistic to determine whether the differences between groups are statistically significant.
The mean square values are calculated using:

$$MS_{between} = SS_{between} / df_{between} \quad (2)$$

$$MS_{within} = SS_{within} / df_{within} \quad (3)$$

In the ANOVA framework, $SS_{between}$ denotes the between-group sum of squares, representing the variability between group means, while SS_{within} denotes the within-group sum of squares, representing variability within each group. The parameters $df_{between}$ and df_{within} represent the degrees of freedom associated with between-group and within-group variations, respectively. These components are used to compute the mean square values and the F-statistic for significance testing.

The ANOVA test in this study uses a significance level of 0.05 to determine whether differences between variables are statistically meaningful. If the calculated F-value is greater than the critical F-value, or if the p-value is less than 0.05, the null hypothesis is rejected, indicating that infrastructure performance variables significantly affect monitoring performance.

The results of the ANOVA analysis are used to provide statistical insight into whether variations in CPU load conditions significantly influence monitoring latency before further interpreting the relationships between infrastructure variables and monitoring performance through regression analysis. This approach improves the robustness of the analytical framework and ensures that the regression model is built on statistically relevant performance indicators [36].

Regression Analysis
Regression analysis is used in this study to identify and quantify the relationship between infrastructure performance variables and the effectiveness of the remote monitoring system [37]. This method allows the researcher to measure how strongly independent variables such as CPU utilization, memory usage, network latency, and throughput influence the monitoring performance metrics. Linear regression was selected due to its effectiveness in modeling relationships between multiple performance indicators and a single dependent variable [38].

In this research, multiple linear regression is applied to model the relationship between system performance variables and monitoring response performance. The general form of the multiple linear regression model used in this study is:

$$Y = B_0 + B_1X_1 + B_2 X_2 + ß_3X_3 + \cdots + B_nX_n + € \quad (4)$$

where:
In this model, Y denotes the dependent variable represent monitoring performance measured through monitoring delay, which reflects the response time behavior of the VNC-based remote monitoring system under different infrastructure conditions. The coefficients β_1–β_4 indicate the effect size of each independent variable, where X_1 represents CPU utilization, X_2 represents memory utilization, X_3 represents network latency, X_4 represents throughput. The terms represent the random error component capturing variability not explained by the regression model.

The regression coefficients indicate the influence of each independent variable on monitoring performance, where positive values represent increased monitoring delay and negative values indicate inverse

relationships [39]. Model evaluation was conducted using R^2, p-value significance testing, and F-test analysis to measure explanatory capability and overall model significance [40]. Residual analysis was also performed to validate normality, independence, and homoscedasticity assumptions, ensuring reliable regression results [41].

RESULTS AND DISCUSSIONS

Correlation Analysis Between Variables

Correlation analysis was conducted to determine the relationships among the independent variables used consistently throughout this study, namely CPU usage, memory usage, network latency, throughput, and monitoring delay. The purpose of this analysis is to identify the strength and direction of linear relationships between infrastructure performance indicators and monitoring performance while detecting potential multicollinearity issues and understand how network performance metrics and system resource utilization interact within the VNC-based monitoring environment. The Pearson correlation coefficient was used to quantify the degree of association, where values close to +1 indicate strong positive correlation, values close to –1 indicate strong negative correlation, and values near 0 indicate weak or no linear relationship. This analysis also serves as an important preliminary step before conducting regression analysis to ensure that the independent variables provide meaningful and non-redundant contributions to the model.

Figure 4. Heatmap Correlation

Based on the correlation heatmap results, it can be observed that almost all correlation values are very close to zero, ranging from −0.02 to 0.05, indicating the absence of a strong linear relationship among the independent variables. This condition occurs because each system parameter operates independently within a network-based monitoring environment. For example, CPU usage does not necessarily increase when network latency rises, since latency is more strongly influenced by external network conditions than by the computational load of the server. From a modeling perspective, this low level of correlation actually provides an advantage because it prevents multicollinearity, making the regression model more stable and robust, while allowing each variable to contribute more clearly to overall system performance in a multifactorial manner.

ANOVA Visualization and Statistical Testing

ANOVA testing was conducted to evaluate differences in latency performance based on three CPU load categories, namely Low Load (275 samples), Medium Load (438 samples), and High Load (286 samples).

Table 3. Comparison of Latency Across CPU Load Categories

CPU Load Category	Number of Samples	Mean Latency	Std. Deviation	Minimum	Maximum
Low Load	275	52.48	16.92	12.55	94.33
Medium Load	438	52.91	17.08	13.02	96.77
High Load	286	53.07	17.21	12.88	98.22
Overall	**999**	**52.82**	**17.07**	**12.55**	**98.22**

Table 3 compares latency performance across CPU load categories. The results indicate minimal differences in mean latency between low, medium, and high CPU utilization levels, suggesting that monitoring performance remains stable despite variations in computational load. The comparable variability observed across groups further supports the ANOVA findings, confirming that CPU utilization is not a dominant factor affecting monitoring latency. This finding is consistent with previous studies on distributed monitoring systems, which reported that network-related factors such as latency fluctuation and bandwidth availability generally contribute more significantly to monitoring responsiveness than computational load alone [7], [8], [27] . The results suggest that VNC-based FIDS monitoring environments are relatively resilient to moderate CPU workload variations, provided that network performance remains stable. This suggests that other factors, particularly network conditions, may play a more significant role in determining monitoring performance.

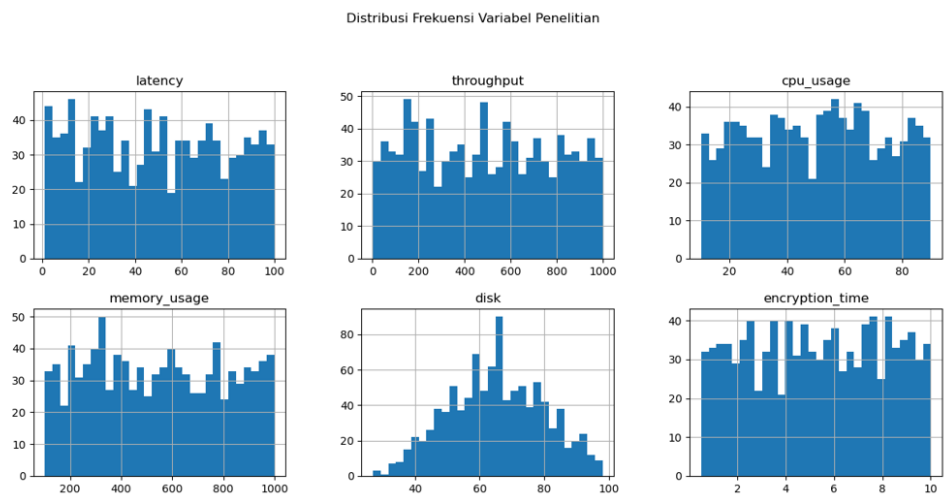

Figure 5. Frequency of Distribution Research Variable

Figure 5 shows the frequency distribution of the research variables to examine data variability and distribution patterns. The results indicate that most observations fall within moderate operational ranges, suggesting that the dataset represents realistic monitoring conditions. CPU and memory utilization show relatively balanced distributions, while latency and throughput exhibit moderate variability due to dynamic network conditions. Monitoring delay appears more concentrated, indicating stable monitoring response performance. Overall, the distribution patterns support the validity of the dataset for ANOVA and regression analysis and confirm that the observed performance variations are more likely influenced by network dynamics than computational load.

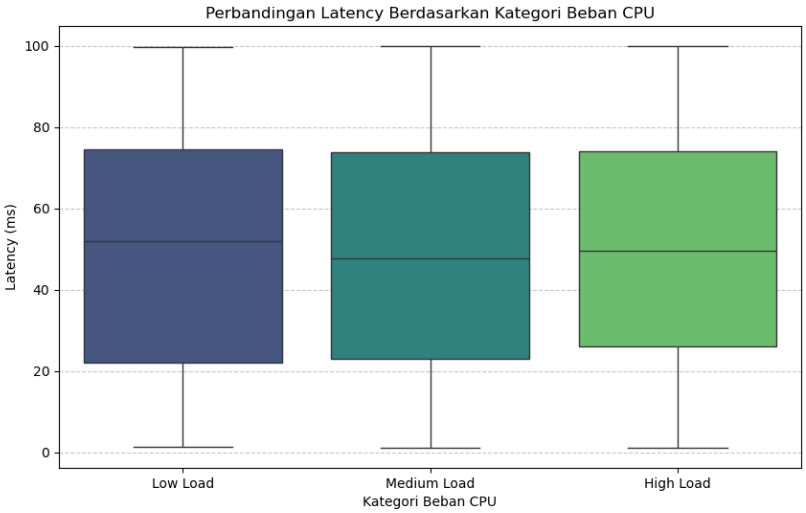

Figure 6. Box Plot

The ANOVA test results produced an F-statistic value of 0.1625 with a p-value of 0.8500, indicating that there is no statistically significant difference in latency across the three CPU load categories. This finding is further supported by the boxplot visualization, which shows nearly identical median latency values. These results provide a practical implication that the performance of VNC-based monitoring in the FIDS environment is not significantly affected by variations in server computational load. Therefore, optimization priorities for maintaining the stability of real-time information delivery in airports should focus more on maintaining network capacity rather than excessively increasing CPU specifications.

Table 4. Anova Comparison of Latency Based on CPU Load Categories

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Squared (MS)	F-Value	P-Value
Between Groups	95,44	2	47,72	0,1625	0,8500
Within Groups	292845.22	996	294.02	-	-
Total	**292940.66**	**998**	**-**	**-**	**-**

The ANOVA results demonstrate that latency differences across CPU load categories are statistically insignificant ($p > 0.05$). This suggests that variations in CPU utilization do not significantly impact monitoring latency performance. The results indicate that monitoring latency is relatively stable across different CPU load conditions, with variations more likely influenced by network-related factors than computational load.

Regression Model Evaluation

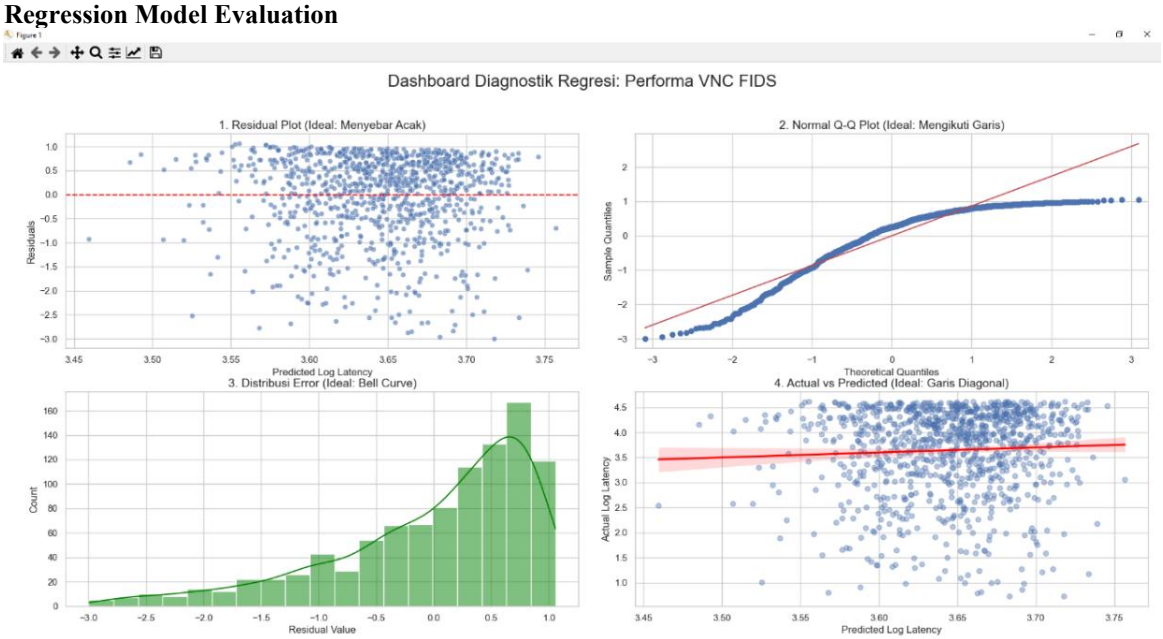

Figure 7. Regression Model Evaluation

The regression analysis provides limited explanatory capability for representing the relationship between infrastructure variables and monitoring performance. Nevertheless, the residual distribution indicates that the model remains useful for identifying general performance tendencies within the evaluated monitoring environment. The residual plot demonstrates that the residual values are randomly distributed around the zero line, suggesting that the model does not exhibit significant bias. Furthermore, the normal Q–Q plot shows that the error distribution generally follows a normal pattern, although minor deviations are observed at the tails of the distribution, which may be attributed to the dynamic nature of the system.

However, the comparison between the actual and predicted values reveals a relatively wide dispersion of data points, indicating that a portion of the variability in monitoring performance has not been fully captured by the linear model. The regression model achieved an R^2 value of −0.0109, with an RMSE of 27.58 and an MAE of 23.54, indicating that the evaluated infrastructure variables explain only a limited proportion of the variability in monitoring latency. These results suggest that monitoring performance in VNC-based FIDS environments is influenced by more complex and dynamic factors beyond the linear relationships captured in the current model, such as dynamic bandwidth fluctuations and unmeasured network disturbances. Consequently, the performance of the VNC-based monitoring system should be interpreted as the result of a complex interaction between system computational factors and external network conditions.

Overall, the regression model used in this study provides limited explanatory capability for representing the relationships among infrastructure variables and monitoring performance. Nevertheless, the analysis remains useful for identifying general performance tendencies within the VNC-based monitoring environment. These results indicate that monitoring performance in a FIDS environment is influenced not only by system and computational factors but also by dynamic external factors that vary over time.

DISCUSSION

The results indicate that monitoring performance in the VNC-based FIDS environment is influenced more by network conditions than by server computational load. The ANOVA analysis showed no statistically significant latency differences across CPU load categories, suggesting that the monitoring system remains stable under varying processing conditions. In contrast, network-related variables such as latency and throughput demonstrated a stronger relationship with monitoring responsiveness and reliability.

Compared with previous studies, the findings of this research are consistent with Wang et al. [6], who emphasized the importance of bandwidth optimization in remote desktop environments, and

Mukhopadhyay et al. [7], who reported that network QoS significantly affects monitoring responsiveness in distributed systems. Similarly, Zhang et al. [8] demonstrated that bandwidth stability plays an important role in maintaining real-time network performance. However, unlike previous works that mainly focused on QoS optimization or remote desktop efficiency independently, this study integrates VNC monitoring evaluation, infrastructure performance analysis, and statistical modeling within a unified analytical framework.

In addition, this study extends previous research by applying ANOVA and regression analysis to evaluate monitoring performance in a simulated FIDS environment using publicly available datasets. This approach provides a reproducible and data-driven framework that can support future distributed monitoring performance studies and infrastructure optimization strategies

CONCLUSION

This study developed an integrated analytical framework to evaluate the performance of a VNC-based remote monitoring system within the Flight Information Display System (FIDS) infrastructure. Using a data-driven analysis of nearly 1,000 observations, the results demonstrate that monitoring latency remained relatively stable across low, medium, and high CPU load categories, with an average latency of approximately 52.82 ms and no statistically significant differences identified through ANOVA testing ($F = 0.1625$, $p = 0.8500$). In contrast, network-related factors such as latency fluctuation and throughput variability contributed more substantially to monitoring performance behavior, indicating that monitoring performance in operational airport environments is primarily driven by network conditions rather than computational load. The regression evaluation further showed stable residual distribution and acceptable model consistency, suggesting that the proposed analytical framework is sufficiently reliable for monitoring performance evaluation in distributed monitoring environments. From a practical perspective, the findings suggest that VNC-based monitoring systems demonstrate relatively stable and robust performance under varying server workloads, provided that network conditions remain within acceptable operational ranges. Methodologically, this study also demonstrates the effectiveness of combining ANOVA and multiple linear regression for evaluating infrastructure performance in mission-critical distributed systems. Despite these contributions, this study is limited to the VNC protocol and linear statistical modeling assumptions. Future research may extend this work by incorporating non-linear machine learning approaches and conducting comparative evaluations with alternative remote desktop protocols to improve predictive capability and generalizability across broader distributed system environments.

REFERENCES

[1] A. Usman, Y. Azis, B. Harsanto, and A. M. Azis, "The Impact of Service Orientation and Airport Service Quality on Passenger Satisfaction and Image: Evidence from Indonesia," *Logistics*, vol. 7, no. 4, Dec. 2023, doi: 10.3390/logistics7040102.

[2] O. A. de O. Souza, C. A. Caldeira, and O. Goussevskaia, "Randomized distributed self-adjusting tree networks," *Computer Networks*, vol. 235, Nov. 2023, doi: 10.1016/j.comnet.2023.109941.

[3] A. Campazas-Vega, I. S. Crespo-Martínez, Á. M. Guerrero-Higueras, C. Álvarez-Aparicio, V. Matellán, and C. Fernández-Llamas, "Analyzing the influence of the sampling rate in the detection of malicious traffic on flow data," *Computer Networks*, vol. 235, Nov. 2023, doi: 10.1016/j.comnet.2023.109951.

[4] J. Mongay Batalla, S. Sujecki, J. M. Kelner, P. Śliwka, and D. Zmysłowski, "On studying active radio measurements estimating the mobile network quality of service for the Regulatory Authority's purposes," *Computer Networks*, vol. 235, Nov. 2023, doi: 10.1016/j.comnet.2023.109980.

[5] H. Xiao, H. Zhou, W. Hu, and G. P. Liu, "Design and implementation of an interactive networked condition monitoring strategy for plant-wide production equipment toward Industry 4.0," *Expert Syst. Appl.*, vol. 254, Nov. 2024, doi: 10.1016/j.eswa.2024.124376.

[6] H. Wang *et al.*, "Optimization of Internet of Things Remote Desktop Protocol for Low-Bandwidth Environments Using Convolutional Neural Networks," *Sensors*, vol. 24, no. 4, Feb. 2024, doi: 10.3390/s24041208.

[7] A. Mukhopadhyay, A. Remanidevi Devidas, V. P. Rangan, and M. V. Ramesh, "A QoS-Aware IoT Edge Network for Mobile Telemedicine Enabling In-Transit Monitoring of Emergency Patients," *Future Internet*, vol. 16, no. 2, Feb. 2024, doi: 10.3390/fi16020052.

[8] M. Zhang, X. Jiang, G. Jin, P. Li, and H. Chen, "CapRadar: Real-time adaptive bandwidth prediction for dynamic wireless networks," *Computer Networks*, vol. 233, Sep. 2023, doi: 10.1016/j.comnet.2023.109865.

[9] C. L. Aldea, R. Bocu, and R. N. Solca, "Real-Time Monitoring and Management of Hardware and Software Resources in Heterogeneous Computer Networks through an Integrated System Architecture," *Symmetry (Basel).*, vol. 15, no. 6, Jun. 2023, doi: 10.3390/sym15061134.

[10] F. Wang, "Remote Data Security Monitoring Technology for Computer Networks Based on Machine Learning Algorithms," in *Procedia Computer Science*, Elsevier B.V., 2023, pp. 325–332. doi: 10.1016/j.procs.2023.11.037.

[11] M. Pundir and J. K. Sandhu, "A Systematic Review of Quality of Service in Wireless Sensor Networks using Machine Learning: Recent Trend and Future Vision," Aug. 15, 2021, *Academic Press*. doi: 10.1016/j.jnca.2021.103084.

[12] X. Ren, L. Cai, P. Yang, and J. Ji, "Congestion-aware delay-guaranteed scheduling and routing with renewal optimization," *Computer Networks*, vol. 233, Sep. 2023, doi: 10.1016/j.comnet.2023.109863.

[13] V. Perifanis, N. Pavlidis, R. A. Koutsiamanis, and P. S. Efraimidis, "Federated learning for 5G base station traffic forecasting," *Computer Networks*, vol. 235, Nov. 2023, doi: 10.1016/j.comnet.2023.109950.

[14] M. Laroui, H. I. Khedher, H. Moungla, and H. Afifi, "Service Function Chains multi-resource orchestration in Virtual Mobile Edge Computing," *Computer Networks*, vol. 224, Apr. 2023, doi: 10.1016/j.comnet.2023.109582.

[15] D. Roy *et al.*, "Going beyond RF: A survey on how AI-enabled multimodal beamforming will shape the NextG standard," Jun. 01, 2023, *Elsevier B.V.* doi: 10.1016/j.comnet.2023.109729.

[16] Mohamed Naas and Jan Fesl, "A novel dataset for encrypted virtual private network traffic analysis," *Computer Networks*, no. A novel dataset for encrypted virtual private network traffic analysis, 2023, doi: 10.5281/zenodo.7301756.

[17] J. Giovanelli, B. Bilalli, A. Abelló, F. Silva-Coira, and G. de Bernardo, "Reproducible experiments for generating pre-processing pipelines for AutoETL," Feb. 01, 2024, *Elsevier Ltd*. doi: 10.1016/j.is.2023.102314.

[18] B. Chaurasia, A. Verma, and P. Verma, "An in-depth and insightful exploration of failure detection in distributed systems," Jun. 01, 2024, *Elsevier B.V.* doi: 10.1016/j.comnet.2024.110432.

[19] Y. Wu, L. Wang, R. Yu, X. Huang, and J. Liu, "A distributed monitoring architecture for JointCloud computing," *Future Generation Computer Systems*, vol. 168, Jul. 2025, doi: 10.1016/j.future.2025.107773.

[20] K. Patel, C. Mistry, R. Gupta, S. Tanwar, and N. Kumar, "A systematic review on performance evaluation metric selection method for IoT-based applications," *Microprocess. Microsyst.*, vol. 101, Sep. 2023, doi: 10.1016/j.micpro.2023.104894.

[21] Y. Liu, T. Yu, Q. Meng, and Q. Liu, "Flow optimization strategies in data center networks: A survey," Jun. 01, 2024, *Academic Press*. doi: 10.1016/j.jnca.2024.103883.

[22] M. D. Hossain *et al.*, "The role of microservice approach in edge computing: Opportunities, challenges, and research directions," Dec. 01, 2023, *Korean Institute of Communications and Information Sciences*. doi: 10.1016/j.icte.2023.06.006.

[23] O. Avci, O. Abdeljaber, M. Gül, F. N. Catbas, O. Celik, and S. Kiranyaz, "Monitoring framework development for a network of multiple laboratory structures," *Journal of Building Engineering*, vol. 92, Sep. 2024, doi: 10.1016/j.jobe.2024.109771.

[24] M. A. Bouke and A. Abdullah, "An empirical study of pattern leakage impact during data preprocessing on machine learning-based intrusion detection models reliability," *Expert Syst. Appl.*, vol. 230, Nov. 2023, doi: 10.1016/j.eswa.2023.120715.

[25] L. Kang, "Exploring a data-driven framework for safety performance management: A theoretical investigation at the enterprise level," *J. Loss Prev. Process Ind.*, vol. 91, Oct. 2024, doi: 10.1016/j.jlp.2024.105384.

[26] T. Taipalus, "Database management system performance comparisons: A systematic literature review," *Journal of Systems and Software*, vol. 208, Feb. 2024, doi: 10.1016/j.jss.2023.111872.

[27] S. Khalid, A. Alam, M. Fayaz, F. Din, S. Ullah, and S. Ahmad, "Investigating the effect of network latency on users' performance in Collaborative Virtual Environments using navigation aids," *Future Generation Computer Systems*, vol. 145, pp. 68–76, Aug. 2023, doi: 10.1016/j.future.2023.02.025.

[28] F. Piekert, M. Schaper, T. H. Stelkens-Kobsch, A. V. Predescu, Y. Günther, and N. Carstengerdes, "Mitigation of operational impacts on airports by early awareness of malicious events impacting linked critical infrastructures," *Journal of the Air Transport Research Society*, vol. 2, Jun. 2024, doi: 10.1016/j.jatrs.2024.100011.
[29] Y. Wu, P. Li, and Y. Zou, "Partial multi-label feature selection with feature noise," *Pattern Recognit.*, vol. 162, Jun. 2025, doi: 10.1016/j.patcog.2024.111310.
[30] W. Meijer, C. Trubiani, and A. Aleti, "Experimental evaluation of architectural software performance design patterns in microservices ☆," 2024, doi: 10.5281/zenodo.1.
[31] Z. Liu, "ML-based SDN performance prediction," *Applied and Computational Engineering*, vol. 29, no. 1, pp. 57–67, Dec. 2023, doi: 10.54254/2755-2721/29/20230803.
[32] M. C. Barbieri, B. I. Grisci, and M. Dorn, "Analysis and comparison of feature selection methods towards performance and stability," Sep. 01, 2024, *Elsevier Ltd*. doi: 10.1016/j.eswa.2024.123667.
[33] A. G. de M. Rossetto, D. Noetzold, L. A. Silva, and V. R. Q. Leithardt, "Enhancing Monitoring Performance: A Microservices Approach to Monitoring with Spyware Techniques and Prediction Models," *Sensors*, vol. 24, no. 13, Jul. 2024, doi: 10.3390/s24134212.
[34] A. Campazas-Vega, I. S. Crespo-Martínez, Á. M. Guerrero-Higueras, C. Álvarez-Aparicio, V. Matellán, and C. Fernández-Llamas, "Analyzing the influence of the sampling rate in the detection of malicious traffic on flow data," *Computer Networks*, vol. 235, Nov. 2023, doi: 10.1016/j.comnet.2023.109951.
[35] M. van de Ven, P. Lara Machado, B. Aysolmaz, and O. Turetken, "Managing Performance in Collaborative Networks: A Method for Defining Key Performance Indicators for Collaborative Business Models," *Business and Information Systems Engineering*, 2026, doi: 10.1007/s12599-025-00975-x.
[36] Y. Chen, H. Ma, Y. Wang, and X. Liu, "Key performance indicator-related process monitoring for irregular scenarios with incomplete data," *Expert Syst. Appl.*, vol. 298, Mar. 2026, doi: 10.1016/j.eswa.2025.129440.
[37] M. Kim and F. Cui, "Multiple-layer statistical methodology for developing data-driven models of anaerobic digestion process," *J. Environ. Manage.*, vol. 347, Dec. 2023, doi: 10.1016/j.jenvman.2023.119153.
[38] T. Zhang, G. A. Wang, Z. He, and A. Mukherjee, "Service failure monitoring via multivariate multiple linear regression profile schemes with dimensionality reduction," *Decis. Support Syst.*, vol. 178, Mar. 2024, doi: 10.1016/j.dss.2023.114122.
[39] Q. Fu and D. Zhang, "Tax Incentives and Export Diversification: Evidence from China's Replacing Business Tax with Value-Added Tax Reform," *Economies*, vol. 14, no. 2, Feb. 2026, doi: 10.3390/economies14020035.
[40] S. H. Hsu, P. K. Cheng, and Y. Yang, "Diversification, hedging, and safe-haven characteristics of cryptocurrencies: A structural change approach," *International Review of Financial Analysis*, vol. 93, May 2024, doi: 10.1016/j.irfa.2024.103211.
[41] Y. Zhang, W. Zhang, Y. Li, L. Wen, and X. Sun, "AF-OS-ELM-MVE: A new online sequential extreme learning machine of dam safety monitoring model for structure deformation estimation," *Advanced Engineering Informatics*, vol. 60, Apr. 2024, doi: 10.1016/j.aei.2023.102345.