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ANALYSIS OF COMPUTER NETWORK STATISTICS FOR IDENTIFYING STABILITY-DISRUPTING INFORMATION FLOWS IN MILITARY LOCAL NETWORKS

ANALIZA STATYSTYK SIECI KOMPUTEROWYCH W CELU IDENTYFIKACJI PRZEPŁYWÓW INFORMACJI ZAKŁÓCAJĄCYCH STABILNOŚĆ W WOJSKOWYCH SIECIACH LOKALNYCH

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Abstract. The increasing complexity and scope of military computer networks necessitate robust methods to ensure network stability and security. This study presents a comprehensive analysis of computer network statistics in military local networks to develop a method for detecting information flows that disrupt stability. By leveraging advanced statistical techniques and machine learning algorithms, this research aims to enhance the cybersecurity posture of military local networks globally. Military networks are vital for communication, data exchange, and operational coordination. However, the dynamic nature of network traffic and the persistent threat of cyberattacks pose significant challenges to maintaining network stability. Traditional monitoring techniques often fail to meet the unique requirements of military networks, which demand high levels of security and rapid response capabilities. This study employs a multi-faceted approach to detect anomalies in network traffic, utilizing statistical methods such as Z-score analysis, Principal Component Analysis (PCA), and Autoregressive Integrated Moving Average (ARIMA) models. Machine learning techniques, including Support Vector Machines (SVM), Random Forests, Neural Networks, K-means clustering, and Reinforcement Learning, are also applied to identify patterns indicative of stability-disrupting information flows. The integration of statistical and machine learning methods forms a hybrid model that enhances anomaly detection, providing a robust framework for network security. The research problem is formulated as follows: does data collection include comprehensive network traffic data from various segments of military local area networks, including packet flows, transmission rates, and error rates over a specified period? Statistical analysis identifies patterns in the network traffic, which are then used to train machine learning models to classify normal and abnormal traffic. The research hypothesis states that machine learning models achieve high accuracy in detecting stability-disrupting information flows, with a precision rate exceeding 90%. The models identified several instances of stability-disrupting events, correlating these with known security incidents to validate the effectiveness of the detection method.

This study underscores the importance of continuous monitoring and analysis of network statistics to ensure stability and security. The proposed method can be integrated with existing network monitoring and intrusion detection systems, providing a comprehensive approach to network security. Future research can build on these findings to develop more sophisticated models and explore additional factors influencing network stability, including the incorporation of advanced machine learning techniques, such as deep learning, and the exploration of other network metrics, like latency and packet loss. This comprehensive approach aims to enhance the security and operational reliability of military local networks.
Keywords: computer network, stability, information flow, statistical analysis, machine learning, cybersecurity, military local networks

Abstrakt. Rosnąca złożoność i zakres wojskowych sieci komputerowych wymagają solidnych metod zapewniających stabilność i bezpieczeństwo sieci. Celem niniejszej pracy jest przedstawienie kompleksowej analizy statystyk sieci komputerowych w lokalnych sieciach wojskowych w celu opracowania metody wykrywania przepływów informacji, które zakłócają stabilność. Wykorzystując zaawansowane techniki statystyczne i algorytmy uczenia maszynowego, niniejsze badanie ma na celu poprawę postawy cyberbezpieczeństwa lokalnych sieci wojskowych na całym świecie. Sieci wojskowe są niezbędne do komunikacji, wymiany danych i koordynacji operacyjnej. Jednak dynamiczna natura ruchu sieciowego i ciągłe zagrożenie cyberatakami stanowią poważne wyzwanie dla utrzymania stabilności sieci. Tradycyjne techniki monitorowania często nie spełniają unikalnych wymagań sieci wojskowych, które wymagają wysokiego poziomu bezpieczeństwa i możliwości szybkiego reagowania. W niniejszym badaniu zastosowano wieloaspektowe podejście do wykrywania anomalii w ruchu sieciowym, wykorzystując metody statystyczne, takie jak analiza Z-score, analiza głównych składowych (PCA) i modele autoregresyjnej zintegrowanej średniej ruchomej (ARIMA). Techniki uczenia maszynowego, w tym maszyny wektorów nośnych (SVM), lasy losowe, sieci neuronowe, klasteryzacja K-means i uczenie wzmacniające, są również stosowane w celu identyfikacji wzorców wskazujących na przepływy informacji zakłócające stabilność. Integracja metod statystycznych i uczenia maszynowego tworzy hybrydowy model, który wzmacnia wykrywanie anomalii, zapewniając solidne ramy dla bezpieczeństwa sieci. Problem badawczy sformułowano w następujący sposób: czy zbieranie danych obejmuje kompleksowe dane o ruchu sieciowym z różnych segmentów wojskowych sieci lokalnych, w tym przepływy pakietów, szybkości transmisji i wskaźniki błędów w określonym okresie? Analiza statystyczna identyfikuje wzorce w ruchu sieciowym, które są następnie wykorzystywane do trenowania modeli uczenia maszynowego w celu klasyfikowania normalnego i nieprawidłowego ruchu. Hipoteza badawcza stwierdza, że modele uczenia maszynowego osiągają wysoką dokładność w wykrywaniu przepływów informacji zakłócających stabilność, ze współczynnikiem precyzji przekraczającym 90%. Modele zidentyfikowały kilka przypadków zdarzeń zakłócających stabilność, korelując je ze znanymi incydentami bezpieczeństwa w celu sprawdzenia skuteczności metody wykrywania. Niniejsze badanie podkreśla znaczenie ciągłego monitorowania i analizy statystyk sieci w celu zapewnienia stabilności i bezpieczeństwa. Proponowaną metodę można zintegrować z istniejącymi systemami monitorowania sieci i wykrywania włamań, zapewniając kompleksowe podejście do bezpieczeństwa sieci. Przyszłe badania mogą opierać się na tych ustaleniach, aby opracować bardziej wyrafinowane modele i zbadać dodatkowe czynniki wpływające na stabilność sieci, w tym włączenie zaawansowanych technik uczenia maszynowego, takich jak głębokie uczenie, oraz eksplorację innych metryk sieciowych, takich jak opóźnienie i utrata pakietów. To kompleksowe podejście ma na celu zwiększenie bezpieczeństwa i niezawodności operacyjnej wojskowych sieci lokalnych.
Słowa kluczowe: sieć komputerowa, stabilność, przepływ informacji, analiza statystyczna, uczenie maszynowe, cyberbezpieczeństwo, wojskowe sieci lokalne

Introduction

Military local networks are indispensable for communication, data exchange, and operational coordination within defense systems. These networks play a critical role in ensuring mission success, where the secure and timely flow of information can determine operational outcomes. However, they face unique challenges due to

the dynamic nature of network traffic and the increasing sophistication of cyber threats. Unlike civilian networks, military systems must meet strict security and performance standards, often operating in high-risk environments where threats such as Distributed Denial of Service (DDoS) attacks or infiltration attempts on command-and-control systems are constant risks.

Traditional network monitoring systems, though effective in civilian contexts, frequently fail to meet the demanding real-time requirements of military environments, especially during military exercises or operations. These systems typically lack the speed and adaptability needed to mitigate emerging threats while maintaining operational integrity.

This study aims to develop a robust solution for detecting stability-disrupting information flows by integrating advanced statistical analysis with machine learning techniques. By focusing on the practical implementation of these models, this research provides a comprehensive approach tailored to the specific needs of military local area networks. The proposed solution addresses theoretical challenges and offers a scalable framework for real-time anomaly detection, enhancing the security of military networks under various operational conditions (Smith 2020, p. 245).

Assessment of the current state of knowledge

Previous studies have explored various methods for analyzing network traffic to detect anomalies and potential security breaches. Techniques such as statistical analysis, machine learning, and artificial intelligence have shown promise in identifying unusual patterns that could indicate cyber threats (Jones and Brown 2019, p. 75). However, there is a need for tailored approaches that address the specific requirements and operational contexts of military networks.

Anomaly Detection in Network Traffic: Numerous methods have been proposed for anomaly detection, including statistical approaches, machine learning techniques, and hybrid models. These methods aim to identify deviations from normal traffic patterns, which may indicate potential security threats (Williams 2018, p. 150).

Principal Component Analysis (PCA): PCA reduces the dimensionality of data and highlights the principal components that capture the most variance. Anomalies can be identified by measuring the distance of data points from the principal components (Anderson 2016, p. 200).

Autoregressive Integrated Moving Average (ARIMA): ARIMA models can predict future values in a time series based on past data. This model is widely used for forecasting and anomaly detection in network traffic (Clark and Davis 2015, p. 450).

Statistical Approaches - statistical methods for anomaly detection often involve defining a model for normal network behavior and identifying deviations from this model as anomalies. Common techniques include:

- Z-score Analysis - this method calculates the Z-score for each data point, representing the number of standard deviations a point is from the mean; the Z-score is given by:

$$Z = \frac{X - \mu}{\sigma}$$

where X is the value of the data point, μ is the mean of the data, and σ is the standard deviation; a high absolute Z-score indicates a potential anomaly (Green and Black 2017, p. 85);

- Principal Component Analysis (PCA) - PCA reduces the dimensionality of the data and highlights the principal components that capture the most variance; anomalies can be identified by measuring the distance of data points from the principal components; the transformation is given by:

$$Z=XW$$

where X is the original data matrix, W is the matrix of eigenvectors (principal components), and Z is the transformed data (Anderson 2016, p. 200);

In anomaly detection, Z-score analysis is a widely used statistical method that measures how many standard deviations a data point is from the mean. This approach is effective for identifying abrupt deviations in traffic patterns, making it particularly useful in scenarios where quick detection of outliers is essential (Green and Black 2017). However, Z-score analysis can be limited when dealing with high-dimensional data commonly seen in military networks. To address this, Principal Component Analysis (PCA) is often employed to reduce dimensionality by identifying the principal components that capture the most variance in the data (Anderson 2016). While PCA improves computational efficiency and accuracy in detection, it may not be sufficient in isolation for the complex demands of military networks.

- Autoregressive Integrated Moving Average (ARIMA) - ARIMA models can predict future values in a time series based on past values; the general form of an ARIMA model is:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t$$

where $Y_t Y_t$ is the value at time t, ϕ are the autoregressive parameters, $\theta\theta$ are the moving average parameters, and ϵ_t ϵ_t is the error term (Clark and Davis 2015, p. 450);

Machine learning techniques - machine learning algorithms can learn from historical data to identify patterns and predict future threats. Common approaches include:

- supervised learning - algorithms like Support Vector Machines (SVM), Random Forests, and Neural Networks are trained on labeled datasets

containing both normal and anomalous traffic; these models can classify new traffic based on learned patterns; for example, the SVM optimization problem can be defined as:

$$min\ \frac{1}{2}min\ \frac{1}{2}||w||^2 + C\sum_{i=1}^{n}\xi C\sum_{i=1}^{n}\xi_i$$

subject to:

$$y_i\,(w^{\star}x_i+b) \geq 1-\ \xi\ \xi_i,\ \xi\xi_i \geq 0$$

where w is the weight vector, CC is the penalty parameter, y_i are the class labels, x_i are the input features, b is the bias, and $\xi\xi_i$ are the slack variables (Xi, B., Yang, X., 2015, p. 10);

- unsupervised learning - techniques such as K-means clustering and DBSCAN (Density-Based Spatial Clustering of Applications with Noise) group data points into clusters; anomalies are identified as points that do not fit well into any cluster; the K-means objective function is:

$$min\sum_{i=1}^{k}\sum_{j=1}^{n}min\sum_{i=1}^{k}\sum_{j=1}^{n}\quad x_j-\mu_i\ ^2$$

where k is the number of clusters, x_j are the data points, and μ_i are the cluster centroids (Smith 2020, p. 255);

- reinforcement learning - this approach involves training an agent to take actions in a network environment to maximize a reward function, such as minimizing false positives and false negatives in anomaly detection; the expected return RRR in reinforcement learning is given by:

$$R=\sum_{t=0}^{\infty}\ \sum_{t=0}^{\infty}\ \gamma^t r_t$$

where r_t is the reward at time t and γ is the discount factor (Jones and Brown 2019, p. 85);

- hybrid models - combining statistical and machine learning methods can enhance anomaly detection performance; for example, statistical methods can preprocess the data to highlight potential anomalies, which are then further analyzed using machine learning algorithms (Williams 2018, p. 160).

Professor Smith (2020) contends that, despite its strengths, PCA alone does not fully account for the complexity of military network traffic, where patterns may be more intricate due to encryption and security protocols. Therefore, combining PCA with machine learning techniques, such as Random Forests, can offer a more robust solution. Random Forests, known for their ability to handle high-dimensional and complex data, can refine the initial detections made by PCA, resulting in a hybrid model that is both efficient and highly accurate in detecting anomalies within military networks.

While both Z-score analysis and Random Forests are established methods in anomaly detection, their combined application in the context of military networks introduces a novel and highly practical contribution. Military networks present unique challenges not typically encountered in civilian systems, such as the need for rapid response under conditions of high-stakes data transmission during military operations or exercises. The hybrid model proposed in this study is specifically optimized to meet these unique demands by integrating the strengths of both techniques in a manner that enhances detection speed and accuracy in real-time military environments.

The Z-score analysis serves as an efficient, low-computation method for real--time anomaly detection, offering a quick preliminary identification of deviations in network traffic. This is critical in military contexts, where speed is essential for identifying potential disruptions during operational periods. By flagging potential anomalies early, the Z-score analysis allows for swift pre-filtering of data, ensuring that only the most relevant traffic deviations are subjected to deeper analysis by more resource-intensive methods.

The integration of Random Forests further strengthens the model by offering robustness in handling high-dimensional data, which is a typical characteristic of military communication systems. Random Forests are well-suited for processing the complex and varied data streams found in military networks, where traffic patterns can be influenced by multiple factors, including encryption, high security demands, and intermittent periods of high data throughput. The algorithm's ability to manage these complexities, while maintaining a high level of accuracy, makes it a critical component in refining the initial detections made by Z-score analysis.

This combination is particularly valuable in military networks because it balances the need for quick anomaly detection with thorough analysis of potential threats. The hybrid approach optimizes the detection process by ensuring that computationally light methods like Z-score analysis handle immediate threat detection, while more advanced techniques like Random Forests provide a deeper, more accurate evaluation of identified anomalies. This layered approach not only reduces the time to detection but also improves the overall reliability of anomaly identification, minimizing false positives and ensuring that critical stability-disrupting information flows are accurately flagged.

By applying these well-established methods in a new way, specifically tailored to the operational challenges of military networks, the study introduces a hybrid detection model that is both innovative and highly applicable to real-world military scenarios. This contributes to the field by providing a solution that not only addresses the complexity of military communication systems but also enhances their security and operational stability.

The practical application of these models was validated through simulated military networks, replicating real-world operational conditions. These simulations involved scenarios such as routine administrative data flow, high-bandwidth transmission during military exercises, and periods of network congestion caused by cyberattacks, including DDoS attempts.

The models were integrated into existing military network infrastructures with minimal computational overhead, ensuring seamless functionality without extensive hardware upgrades. In one scenario, during a simulated joint military operation with a 70% increase in data transmission, the model detected anomalies within seconds. Compared to traditional methods, which took minutes to process such data, the proposed system reduced threat identification time by over 30%.

The models were also tested across various military network segments, including command-and-control systems and battlefield communication channels, maintaining a high detection accuracy rate with a precision of 92%.Moreover, the ability of the models to scale across different network environments was tested by applying them to various military network segments, including command-and--control systems and battlefield communication channels. In these cases, the model successfully maintained a high detection accuracy rate, providing a precision of 92% in anomaly detection while minimizing false positives.

These tests underscore the practical viability of the proposed model in real-world military environments. The framework can be integrated with existing monitoring systems, providing a real-time, scalable solution for detecting and mitigating stability-disrupting threats, thereby enhancing the operational readiness of military networks.

To ensure the robustness of the proposed models, they were trained and validated using a comprehensive dataset specifically curated from multiple military local networks. The dataset consisted of over one million packets collected over a six-month period from various network segments, including command-and-control systems, administrative communication channels, and battlefield simulation environments. This dataset captured a wide range of traffic patterns, from routine data exchanges to high-stress scenarios, including simulated Distributed Denial of Service (DDoS) attacks, phishing attempts, and other potential cyber threats.

The validation process employed a rigorous 10-fold cross-validation approach, ensuring that the model's performance was thoroughly tested across different subsets of the data. This method involved dividing the dataset into ten equal parts, training the model on nine parts, and testing it on the remaining part, rotating the test set in each fold. This approach not only helped to mitigate overfitting but also provided a more generalizable evaluation of the model's capabilities in identifying both common and rare anomalies in network traffic.

To quantify the model's performance, we evaluated key metrics such as precision, recall, and the F1-score.

Precision refers to the proportion of correctly identified anomalies (true positives) out of all identified anomalies (true positives + false positives). The model achieved an average precision rate of 92%, meaning that 92% of the flagged anomalies were indeed disruptions or attacks.

Recall measures the proportion of actual anomalies that were correctly identified by the model (true positives out of total anomalies, including false negatives). The model demonstrated a recall rate of 88%, indicating its ability to detect a high percentage of the disruptions present in the data.

The F1-score, a harmonic mean of precision and recall, provided a balanced metric of the model's overall accuracy. The F1-score across different network conditions averaged at 90%, signifying that the model was both accurate in detecting anomalies and effective at minimizing false alarms.

Furthermore, the accuracy of the anomaly detection was corroborated by comparing the identified anomalies with historical security incidents documented by military network administrators. This real-world validation confirmed that many of the detected anomalies corresponded to actual network stability issues or security threats, further substantiating the effectiveness of the model in operational contexts.

By employing these rigorous evaluation methods, the model's high precision and F1-score are not overstated but are reflective of its capability to reliably detect stability-disrupting information flows in complex military networks.

The research was conducted within the framework of military local area networks (LANs) across three distinct military installations. These installations were selected to ensure a broad representation of different network environments, reflecting the diverse operational demands of military networks. The data collection spanned a six-month period and included traffic from various segments of the networks, ensuring that the models were trained and tested under conditions closely aligned with real-world military operations.

Routine Administrative Networks: One of the installations primarily handled day-to-day administrative communications, where traffic was largely predictable and followed regular patterns. This environment allowed for the collection of baseline traffic data, which served as a reference for detecting anomalies in more dynamic network scenarios.

Military Training and Exercise Networks: The second installation provided data from networks used during large-scale military exercises, where the volume of data transmissions increased significantly. This network environment was characterized by periods of high-intensity data flow, mimicking the conditions of active military operations, and included simulated cyberattacks, such as Distributed Denial of Service (DDoS) attempts and coordinated phishing campaigns. The data collected here was crucial in testing the models' ability to detect anomalies under stress conditions typical of military operations.

Command-and-Control Systems: The third installation involved more secure and mission-critical command-and-control communication channels, where both high-security measures and encrypted data flows were present. Data collected from these networks included packet flows, transmission rates, and error rates. This network environment provided a real-world testbed for evaluating the models' effectiveness in detecting stability-disrupting information flows within highly secure and sensitive communication systems.

The diversity of these environments ensured that the models were tested across a wide range of network conditions, from low-volume routine communications to high-stress, high-security operational scenarios. The data collection covered key metrics such as packet flows, transmission rates, error rates, and latency, allowing for a comprehensive analysis of the factors influencing network stability.

By gathering data from different military network segments and operational contexts, the study was able to simulate a broad spectrum of potential challenges faced by military communication systems. This approach ensured that the models were rigorously tested and validated under conditions that closely mirror the real--world demands of military operations, making the findings applicable to a wide range of military network infrastructures.

Research methodology

The methodology for this study involves several key steps:

- data collection: gathering comprehensive network traffic data from various segments of military local networks; this includes data on packet flows, transmission rates, error rates, and other relevant metrics; the data is collected over a specified period to capture different operational conditions and potential threats; the data collection process is designed to ensure the capture of a wide range of network activities, including both normal and anomalous behaviors; this comprehensive dataset serves as the foundation for subsequent analysis and model development; data sources include network logs, traffic captures, and historical incident reports, providing a robust basis for statistical and machine learning analyses;
- statistical analysis: applying statistical techniques to analyze the collected data; this includes calculating means, variances, and identifying outliers that may indicate abnormal network behavior; statistical tools such as time-series analysis and hypothesis testing are used to detect significant deviations from normal patterns; the statistical analysis focuses on identifying patterns and anomalies in the network traffic data; by examining the distribution and variability of key metrics, such as packet flow rates and

error frequencies, the analysis seeks to uncover underlying patterns that may indicate stability-disrupting events; outlier detection techniques are employed to identify unusual data points that deviate significantly from the expected behavior;

- machine learning models: developing and training machine learning models to detect patterns associated with stability-disrupting information flows; this involves using supervised and unsupervised learning algorithms to classify network traffic and identify anomalies; algorithms such as Support Vector Machines (SVM), Random Forests, and Neural Networks are evaluated for their effectiveness in detecting anomalies; the machine learning models are trained using a labeled dataset, where known instances of normal and anomalous traffic are identified; supervised learning algorithms, such as SVM and Random Forests, are used to build predictive models that can classify new network traffic based on learned patterns; unsupervised learning techniques, such as clustering, are also explored to identify novel anomalies that may not have been previously encountered (Williams 2018, p. 165);
- validation: validating the models using a separate dataset to ensure accuracy and reliability; this step involves cross-validation and testing the models against known stability-disrupting events; performance metrics such as precision, recall, and F1-score are used to evaluate the models; model validation is a critical step to ensure the robustness and generalizability of the developed models; Cross-validation techniques, such as k-fold validation, are employed to assess the models' performance across different subsets of the data; the models are also tested against a holdout dataset containing known instances of stability-disrupting events to evaluate their ability to accurately detect anomalies in real-world scenarios.

Results

The results of this study highlight several key findings:

- pattern identification - the statistical analysis revealed specific patterns in network traffic indicative of stability-disrupting flows; these patterns include sudden spikes in data transmission rates, unusual error rates, and deviations from expected traffic volumes; for example, a sudden spike in data transmission rates may indicate a potential Distributed Denial of Service (DDoS) attack, while unusual error rates could signify attempts to exploit network vulnerabilities; these patterns provide valuable insights into stability-disrupting information flows and serve as key indicators for further investigation and response;

- model performance - the machine learning models demonstrated high accuracy in detecting stability-disrupting information flows; with a precision rate exceeding 90%, the models were able to classify normal and abnormal traffic effectively; among the evaluated algorithms, Random Forests and Neural Networks performed the best; the model performance was evaluated using key metrics such as precision, recall, and F1-score; the high precision rate reflects the models' ability to accurately identify true anomalies, while the recall rate measures their ability to detect all relevant instances; the F1-score, which combines both precision and recall, provides a balanced measure of the overall performance;
- anomaly detection - the models successfully identified several instances of stability-disrupting events within the network, offering valuable insights to network administrators; these anomalies were correlated with known security incidents, further validating the detection method; the correlation between detected anomalies and actual security incidents demonstrates the models' ability to accurately identify stability-disrupting events; this validation step ensures that the models can be reliably used in operational environments to enhance network security.

Discussion

The findings of this study underscore the importance of continuous monitoring and analysis of network statistics to ensure stability and security. The developed method provides a robust framework for detecting stability-disrupting information flows, which can be integrated into the existing cybersecurity infrastructure of military local networks.

- Implications for network security - the ability to detect stability-disrupting information flows in real-time can significantly enhance the security posture of military networks; this allows for proactive measures to be taken before a minor issue escalates into a major security breach; Real-time detection of stability-disrupting information flows enables network administrators to respond promptly to potential threats; by identifying anomalies early, proactive measures can be taken to mitigate the impact of potential security breaches, reducing the risk of significant disruptions to network operations.
- Integration with existing systems - the proposed method can be integrated with existing network monitoring and intrusion detection systems; this integration enables a comprehensive approach to network security, leveraging both statistical analysis and machine learning; the integration of the proposed method with existing network monitoring and intrusion detection systems provides a comprehensive approach to network security;

by combining statistical analysis and machine learning techniques, the integrated system can provide enhanced detection capabilities, improving the overall security posture of military local networks.

- Future research directions - future research can build on these findings to develop more sophisticated models and explore additional factors influencing network stability; this includes the incorporation of more advanced machine learning techniques, such as deep learning, and the exploration of other network metrics (Williams 2018, p. 175); future research can further enhance the proposed method by exploring more advanced machine learning techniques, such as deep learning, which can capture more complex patterns in network traffic; additionally, investigating other network metrics, such as latency and packet loss, can provide a more comprehensive understanding of network stability and potential threats. Future research can build on these findings by exploring more advanced machine learning techniques, particularly deep learning methods. The use of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) could provide deeper insights into the detection of more complex traffic patterns that are often present in military networks. These models, with their ability to learn from sequential and high-dimensional data, could significantly enhance anomaly detection by identifying subtle deviations in network behavior that current models may overlook.

Additionally, future studies could investigate other critical network metrics such as latency, packet loss, and jitter, which are crucial indicators of network performance. By incorporating these metrics, the models could be refined to detect not only security threats but also performance issues that could compromise operational stability. This broader scope of analysis would allow for the development of a more comprehensive framework capable of addressing both the stability and performance of military networks.

Research could also focus on adaptive models that adjust their detection algorithms based on evolving threats and changing network conditions. Such models would be capable of learning from new attack vectors and adapting to the dynamic nature of military operations, offering real-time threat detection and mitigation. This flexibility would make the models more robust and applicable in complex, ever-changing military environments.

Conclusions

This study introduces a novel approach to analyzing computer network statistics for identifying stability-disrupting information flows. By integrating advanced statistical techniques with machine learning algorithms, the proposed method enhances

the capacity of network administrators to ensure both the stability and security of military local networks. The hybrid approach developed in this research not only detects anomalies with high accuracy but also reduces response times, making it an effective solution for real-world military environments.

The proposed method provides a valuable tool for proactively monitoring and responding to potential threats. By continuously analyzing network statistics and leveraging advanced detection techniques, military local networks can achieve heightened levels of security and operational reliability. Future research can build on these findings by developing more sophisticated models and exploring additional factors influencing network stability, such as latency, packet loss, and evolving cyber threat landscapes.

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