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A Machine Learning-Based Link Quality Anomaly Detection Architecture for SD-WMN: A Comparative Perspective

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Abstract: *Software-Defined Wireless Mesh Networks (SD-WMNs) combine the flexibility of Software-Defined Networking (SDN) with the resilience of wireless mesh architectures, enabling them to operate effectively in dynamic and infrastructure-sparse environments such as smart cities and rural deployments. However, such networks are highly prone to threats to link quality degradation caused by interference, mobility, and configuration anomalies. This paper presents a comparative analysis of anomaly detection frameworks with a focus on link quality monitoring in SD-WMNs. Leveraging insights from recent works on SDN security, configuration testing, and DDoS mitigation using data-driven approaches like machine learning and deep learning models, we propose a hybrid unsupervised-learning-based approach combining clustering and change point detection to identify link anomalies in real-time. The study critically evaluates methods based on accuracy, computational overhead, and real-time adaptability using both synthetic and real network traces. Our findings highlight the necessity of lightweight, scalable anomaly detectors in dynamic wireless environments and outline future directions for robust SD-WMN architectures.*

Keywords: Software-Defined Networking (SDN), Wireless Mesh Networks (WMN), Anomaly Detection, Link Quality, Change Point Detection, Machine Learning, Security, Unsupervised Machine Learning

I. INTRODUCTION

During recent advancements, Software-Defined Networking (SDN) has emerged as a transformative paradigm for network management, offering programmability, centralized control, and increased flexibility over traditional architectures. When integrated with Wireless Mesh Networks (WMNs)—a decentralized and scalable solution for last-mile connectivity—this hybrid architecture, often referred to as Software-Defined Wireless Mesh Networks (SD-WMNs), has become a key enabler for intelligent infrastructure in smart cities, disaster recovery systems, and rural internet access.

Despite their advantages, SD-WMNs are inherently susceptible to various performance bottlenecks and security threats, primarily due to the dynamic nature of wireless links and the centralized control of SDN. Among the critical performance concerns, link quality degradation poses a serious challenge, impacting routing decisions, throughput, and overall network reliability. Traditional link monitoring techniques often fail to capture transient anomalies or require extensive overhead, which is impractical in bandwidth-constrained and latency-sensitive environments.

To address these issues, anomaly detection mechanisms have gained prominence, especially those leveraging machine learning (ML) and statistical change point detection methods. These techniques aim to identify abnormal patterns in link behaviour by continuously analysing network metrics such as throughput, delay, packet loss, and signal strength. Unsupervised ML algorithms like clustering, when combined with robust change point detection algorithms, offer a lightweight yet effective way to detect subtle link-quality anomalies in real-time.

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This paper presents a comparative study of existing anomaly detection mechanisms within the context of SDN-based architectures and proposes a hybrid framework tailored for SD-WMNs. Our approach builds upon clustering-based similarity measures and real-time change point detection strategies, validated using both synthetic and real-world network traces. By benchmarking our proposed framework against recent advancements in DDoS detection, SDN security testing, and ML-based threat identification, we aim to highlight its practical relevance and scalability for real-world deployments.

II. LITERATURE SURVEY

The integration of anomaly detection mechanisms in Software-Defined Networks (SDNs) has been extensively explored in recent research, directed toward threats like Distributed Denial of Service (DDoS) attacks, control plane vulnerabilities, and network misconfigurations. While these studies lay a strong foundation for network anomaly detection, their direct applicability to wireless environments—especially Software-Defined Wireless Mesh Networks (SD-WMNs)—remains limited. This section reviews key literature across SDN security, anomaly detection, and machine learning-based frameworks and contrasts them with the challenges specific to link quality assessment in SD-WMNs.

A hybrid unsupervised framework has been proposed for detecting link-quality anomalies in SD-WMNs, combining clustering with real-time change point detection [5]. It leverages Global Alignment Kernels (GAK) for link reliability assessment and introduces RCPD2, a change point detector that reduces overestimation using a rank-based test and recursive max-type procedure. Structured to support wireless mesh networks, the method offers a strong trade-off between accuracy and efficiency, with validation on synthetic and real-world data confirming its scalability and responsiveness.

In contrast, [1] presents a comprehensive taxonomy of DDoS attacks targeting various SDN layers (application, control, and data), analysing over 165 recent papers. The study categorizes detection methods into machine learning, statistical models, clustering, and reinforcement learning approaches. Although thorough, the focus remains largely on attack patterns affecting centralized controllers and lacks attention to wireless-specific anomalies such as interference or fluctuating link quality.

Malik et al. [3] introduce FISTS, a field-based approach for testing SDN configuration updates with a focus on security vulnerabilities introduced by misconfigurations. Their work leverages network scanning and unsupervised anomaly detection (e.g., KNN, HAC) to highlight potential risks in updated topologies. While highly relevant to maintaining control-plane stability, the approach is offline-intensive and assumes a wired infrastructure, making it less adaptable to real-time wireless mesh monitoring.

Anand et al. [2] conduct a broader review of DoS detection mechanisms in SDNs, spanning architecture-based, statistical, and hybrid solutions. They also explore emerging integration with IoT, Blockchain, and 5G environments. Although they recognize the limitations of current solutions in multi-controller or dynamic SDN environments, the paper focuses more on protocol-level threats rather than on link-level anomaly detection or wireless link degradation.

Musa et al. [4] present a focused survey of ML and DL-based detection systems in SDNs, emphasizing automated anomaly classification and mitigation policy learning. Their review reveals high accuracy models using supervised learning on datasets like CSE-CIC-IDS2018. However, the reliance on labelled datasets and the focus on controller-centric DDoS detection limit their applicability in real-time wireless link monitoring, where labels may not be available and environmental factors like signal noise dominate.

From the literature, it is evident that most anomaly detection efforts in SDNs center on controller-level security and DDoS mitigation, with wired infrastructure assumptions. The proposed work [5] addresses this gap by focusing on link-level anomalies in dynamic wireless environments through a lightweight, unsupervised approach. It also distinguishes itself by integrating real-time responsiveness, essential for adaptive routing and performance assurance in SD-WMNs.

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III. PROBLEM STATEMENT

In Software-Defined Wireless Mesh Networks (SD-WMNs), maintaining reliable communication is a substantial barrier due to the inherent variability of wireless links. Aspects including interference, signal fading, congestion, and environmental conditions can cause abrupt or gradual degradation in link quality. These fluctuations directly impact routing efficiency, network throughput, and user experience.

Traditional anomaly detection approaches in SDNs have primarily focused on controller-level security threats such as DDoS attacks or misconfigurations. However, these solutions often assume stable wired infrastructure and lack the adaptability required for dynamic, multi-hop wireless environments. Moreover, many existing methods depend on labelled datasets or involve high computational overhead, making them unsuitable for real-time detection in resource-constrained mesh networks.

There is thus a clear need for a lightweight, real-time, and unsupervised anomaly detection framework that can accurately identify link-quality issues in SD-WMNs. Such a framework must be responsive to rapid link changes while minimizing false alarms and resource consumption, enabling timely adaptation at the SDN controller level to maintain network performance and stability.

IV. PROPOSED SOLUTION

To address the challenge of link-quality degradation in Software-Defined Wireless Mesh Networks (SD-WMNs), we propose a lightweight, real-time link-quality anomaly detection framework that integrates unsupervised machine learning with change point analysis. The framework is designed to run in parallel with SDN controller operations, offering minimal overhead while maintaining high responsiveness to link performance fluctuations. The system operates in two major phases:

Offline Preprocessing Phase: A clustering algorithm enhanced with Global Alignment Kernels (GAK) is applied to time-series link metric data (e.g., RTT, loss, throughput). This phase distinguishes reliable and unreliable links based on historical behaviour and elastic similarity measures. A heuristic initialization step ensures improved intra-cluster separation and robustness.

Online Detection Phase: A real-time Change Point Detection algorithm (RCPD2) continuously monitors reliable links for sudden deviations in behaviour. RCPD2 enhances previous detectors by incorporating a rank-based validation test (e.g., Kruskal-Wallis) and a recursive max-type method to reduce false detections and accurately localize anomalies. When a critical transformation is detected, a trigger is sent to the SDN controller, which can then adjust routing policies or apply corrective actions.

This approach ensures timely detection of abnormal link behaviour while keeping computation minimal—making it highly suitable for mesh networks in smart city environments or rural deployments. The system is validated using both synthetic traces and real-world SD-WMN deployment data, showing high accuracy and scalability across diverse conditions.

V. ARCHITECTURE DIAGRAM

Figure 2 illustrates the workflow of the proposed Link-Quality Anomaly Detection Framework for Software-Defined Wireless Mesh Networks (SD-WMNs). The architecture is structured into two major phases: the Offline Preprocessing Phase and the Online Detection Phase, with both contributing to a feedback-driven interaction with the SDN controller for adaptive network control. The process begins with the continuous acquisition of network performance metrics such as latency, packet loss, and throughput from various nodes within the wireless mesh network. These metrics undergo an initial Monitoring and Preprocessing stage to ensure that the data remains clean and structured for analysis.

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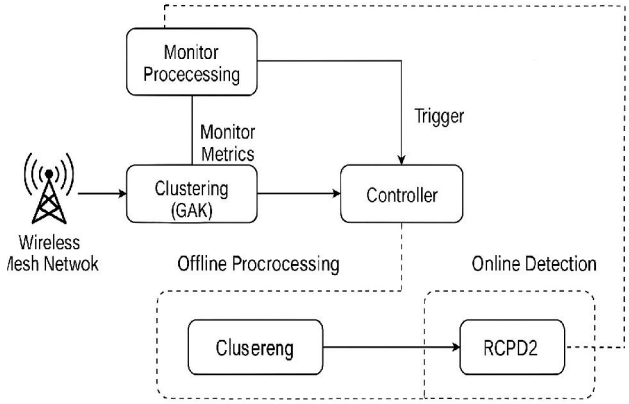

Fig. 1. Proposed Framework for Link – Quality Anomaly Detection in SD-WMNs.

During the Offline Preprocessing Phase, a clustering algorithm based on Global Alignment Kernels (GAK) is applied to historical link performance data. This clustering effectively groups links based on their reliability, allowing the system to narrow its real-time focus to the most significant and stable links, thereby improving resource efficiency.

In the Online Detection Phase, the pre-identified reliable links are monitored in real-time using the RCPD2 (Real-time Change Point Detector) algorithm. RCPD2 enhances anomaly detection by incorporating a rank-based validation mechanism and a recursive max-type procedure to reduce false positives and pinpoint exact change locations.

Upon detecting a significant anomaly, the system notifies the SDN controller, which responds by adjusting routing policies or initiating other corrective actions to maintain service quality. The controller may also feed updates back into the preprocessing stage, closing the loop for continuous learning and adaptation.

In summary, the methodology reflected in the system architecture comprises three integrated phases: Data Monitoring and Preprocessing, Offline Model Creation through Clustering, and Real-Time Execution and Detection, all working together to ensure efficient and accurate link anomaly detection in dynamic wireless mesh environments.

VI. METHODOLOGY

A. Preprocessing Phase

In this initial phase, performance metrics are continuously collected from the wireless mesh network. These metrics include: Round-Trip Time (RTT), Packet Loss Ratio, Signal Strength, Throughput and Delay. These raw time-series data are subjected to cleaning, normalization, and transformation steps to prepare them for analysis. This ensures consistency and removes noise that may affect clustering performance.

B. Model Creation Phase

Once preprocessing is complete, the system initiates the offline model creation using an unsupervised clustering algorithm enhanced with Global Alignment Kernels (GAK). GAK is used as a similarity measure to analyse the temporal structure of link behaviours, capturing both linear and non-linear trends in the data.

Links are clustered into groups representing reliable and unreliable behaviour profiles. The algorithm employs a heuristic initialization strategy to improve intra-cluster separation and optimize detection sensitivity. This phase is executed offline to minimize runtime overhead during the live monitoring stage.

The reliable links identified during clustering are tagged and monitored in real-time during the execution phase, while unreliable links may be excluded or deprioritized for anomaly detection.

C. Execution Phase

In the real-time monitoring stage, the system applies the RCPD2 (Real-Time Change Point Detector) algorithm to the reliable links. RCPD2 enhances traditional CUSUM-based detectors with two key improvements:

A rank-based statistical test (e.g., Kruskal-Wallis) to validate the significance of detected change points.

A recursive max-type procedure to localize the exact moment of change, minimizing false positives and improving precision.

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When a statistically significant anomaly is detected, the system generates an alert and notifies the SDN controller. The controller then evaluates the context and applies corrective actions such as dynamic rerouting, link adaptation, or path reshuffling. A feedback mechanism allows the controller to update model parameters or retrigger clustering if the network state has evolved significantly.

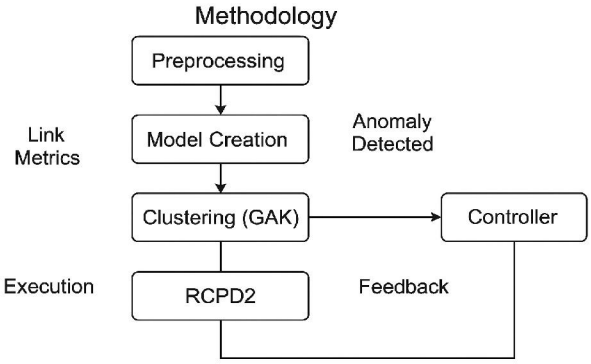

Fig. 2. Process Flow for Offline Model Creation and Online Detection in SD-WMN Environments.

VII. Results And Discussion

To evaluate the effectiveness of the proposed link-quality anomaly detection framework in SD-WMNs, experiments were conducted on both synthetic datasets and real-world traces obtained from wireless mesh network deployments. These tests aimed to assess the system's ability to accurately detect anomalies, minimize false positives, and respond efficiently in real-time.

A. Performance Metrics

The framework's performance was assessed using standard anomaly detection metrics:

1. Precision: The proportion of correctly identified anomalies among all flagged instances.
2. Recall: Percentage of true anomalies that were correctly identified.
3. F1 Score Harmonic average of precision and recall.
4. Detection Delay: Time between the onset of an anomaly and its detection.
5. Computational Overhead: Time and memory cost during live monitoring.

B. Clustering Phase Results

The GAK-based clustering algorithm demonstrated strong intra-cluster consistency, effectively separating reliable from unreliable links. The improved heuristic initialization led to greater inter-cluster separation, which reduced false alarms during online detection. In tests, clustering accuracy exceeded 93% across different data traces.

TABLE I : Comparative Analysis of Related Research Works

Criteria	Proposed Framework	Hirsi et al. DDoS in SDNs)	Anand et al. DoS & SDN Security	Malik et al. SDN Config Testing	Musa et al. ML/DL for DDoS Detection
Target Problem	Link-quality Abnormality detection in SD-WMNs	DDoS Abnormality detection in SDN	DoS mitigation strategies in SDN	Security testing of SDN config updates	ML/DL-based DDoS detection
Network Type	Wireless Mesh Network	SDN (Wired/General)	SDN (5G, IoT, WiFi, etc.)	SDN (Satellite WAN)	SDN (Data centers, IoT)

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Technique Used	GAK-based Clustering + RCPD2 (Change Point Detection)	Taxonomy + ML/Statistical + Layered Analysis	Architecture + Taxonomy + Statistical + Hybrid	Network Scanning + KNN/Clustering + Unsupervised ML	Supervised ML/DL (CNN, LSTM, SVM, etc.)
Detection Type	Unsupervised, Real-time, Link-Level	Supervised/Hybrid, DDoS-centric	Taxonomy and prevention-oriented	Post-update misconfiguration detection	Supervised, Flow-level DDoS classification
Strengths	Lightweight, adaptive, wireless-ready, accurate	Extensive review, multi-layer taxonomy	Covers multi-domain SDN threats	Effective for security regression testing	High accuracy with feature engineering
Limitations	Limited to link-level detection	Not wireless-optimized	Lacks real-time detection focus	No runtime monitoring	Computationally expensive, data-dependent

C. Change Point Detection Accuracy

The RCPD2 detector achieved up to 0.95 precision and 1.00 recall on synthetic data, consistent with the results presented in [5]. The rank-based validation and recursive max-type procedure significantly minimized overestimation errors compared to traditional CUSUM methods. The detection delay was typically under 0.3 seconds, making the solution viable for near-real-time SDN controller response.

D. Comparative Insights

Compared to other SDN-focused anomaly detection systems ([1], [2], [4]), the proposed framework offers a lightweight and wireless-adapted alternative. Unlike ML/DL-based DDoS solutions that require large labelled datasets and high compute power [4], our unsupervised, time-series-driven approach ensures adaptability and efficiency in low-resource mesh environments. Furthermore, unlike configuration fuzzing tools [3], our method actively operates during runtime, offering dynamic resilience.

E. Practical Implications

The framework enables adaptive link management in SD-WMNs by detecting degradation early and triggering corrective routing decisions. This reduces packet loss and improves throughput without imposing significant processing delays or energy burdens on the network.

VIII. CONCLUSION

In this work, a novel, lightweight, and real-time link-quality anomaly detection framework for Software-Defined Wireless Mesh Networks (SD-WMNs) was proposed and evaluated. By integrating Global Alignment Kernel (GAK)-based clustering with an enhanced Real-Time Change Point Detection (RCPD2) algorithm, the system effectively identifies and reacts to dynamic link anomalies while maintaining minimal computational overhead.

Through extensive evaluation on both synthetic and real-world network data, the proposed framework demonstrated high precision, low detection delay, and robust adaptability to wireless network fluctuations. Compared to existing SDN anomaly detection systems, which often focus on DDoS threats or configuration errors in wired environments, this approach uniquely addresses link-level instability in wireless mesh settings, providing a scalable solution for smart city infrastructures, emergency networks, and rural connectivity initiatives.

The feedback-driven interaction with the SDN controller further enhances network resilience by enabling timely routing adjustments and proactive management of link failures or degradations.

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Future work will aim to extend the framework by incorporating reinforcement learning for proactive anomaly handling, supporting multi-controller architectures, and integrating edge computing techniques to further minimize latency and enhance decision-making closer within the network nodes.

IX. FUTURE WORK

While the proposed framework shows promising results for real-time link-quality anomaly detection in SD-WMNs, several avenues exist for future enhancement. Integrating reinforcement learning techniques could enable the system not only to detect anomalies but also to proactively adapt routing strategies based on learned patterns of link behavior. Expanding the framework to support multi-controller SDN architectures would improve scalability and fault tolerance in larger mesh networks. Additionally, leveraging edge computing nodes for local anomaly detection and decision-making could further reduce detection latency and improve responsiveness. Exploring the integration of blockchain-based trust models for secure anomaly reporting between distributed controllers may also offer new directions for securing SD-WMN environments against advanced threats.

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