Journal of Technology Research (JTR)
Volume 3, Special Issue, (2025), pp 602-619 ISSN 3005-639X
The 7th Conference of Engineering Sciences and Technology
(CEST-2025)

Random Forest-Driven Feature Importance Assessment for QoS in MPLS and SD-WAN

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Received: 15-10-2025 | Accepted: 02-12-2025 | Available online: 25-12-2025 | DOI:10.26629/jtr.2025.56

ABSTRACT

This study presents a novel comparative analysis employing Random Forest regression to quantify the relative importance of key Quality of Service (QoS) parameters—packet loss, delay, and jitter—in Multiprotocol Label Switching (MPLS) and Software-Defined Wide Area Network (SD-WAN) architectures. Using empirical data collected from controlled simulations of multimedia traffic, the feature importance scores reveal that packet loss overwhelmingly dominates as the critical factor influencing network performance, with scores of 0.8620 in SD-WAN and 0.7259 in MPLS, indicating an 18.76% increase in SD-WAN's sensitivity to packet loss. Delay exhibits moderate relevance in MPLS, with an importance score of 0.2205, but shows markedly reduced significance in SD-WAN at 0.1341 (a 39.21% decrease). At the same time, jitter demonstrates negligible influence across both networks, with scores below 0.054. These findings confirm that SD-WAN's dynamic path optimisation effectively mitigates delay effects, whereas packet loss remains the principal constraint on performance. This work constitutes the first methodical Random Forest-based comparative evaluation of QoS parameter importance across MPLS and SD-WAN, delivering robust, data-driven insights tailored to each architecture's operational characteristics. The framework provides network operators with critical guidance for targeted QoS optimisation, prioritising packet loss mitigation strategies, particularly within SD-WAN environments. Overall, this research establishes an empirical foundation for architecture-specific QoS management, advancing intelligent network performance assessment through machine learning techniques.

Keywords: feature importance, Quality of Service, network performance, MPLS, SD-WAN, Random Forest, multimedia traffic.

التقييم المعتمد على Random Forest لأهمية الميزات في جودة الخدمة في شبكات (MPLS) وشبكات (SD-WAN)

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ملخـــــــص البحــــــــث

تقدم هذه الدراسة تحليلًا مقارنًا جديدًا باستخدام نماذج الانحدار بغابة عشوائية (Random Forest) لتحديد الأهمية النسبية لمعاملات جودة الخدمة (QoS) الرئيسية — فقدان الحزم، التأخير، والتذبذب الزمني — في هندستَي شبكات تبديل التسمية متعدد البروتوكولات (MPLS) والشبكات الواسعة المعرفة برمجيًا (SD-WAN). باستخدام بيانات تجريبية جُمعت من محاكاة محكمة لحركة مرور الوسائط المتعددة، تُظهر نتائج تقييم أهمية السمات أن فقدان الحزم يهيمن بشكل كبير كعامل حاسم يؤثر على أداء الشبكة، حيث بلغ معدل الأهمية 0.8620 في شبكات SD-WAN و0.7259 في MPLS، ما

يشير إلى زيادة نسبتها 18.76% في حساسية SD-WAN تجاه فقدان الحزم. أما التأخير فأظهر أهمية متوسطة في MPLS بمعدل أهمية 0.2205، ولكنه كان أقل كثيرًا في SD-WAN بمعدل 0.1341 (بانخفاض نسبته 39.21%). في الوقت نفسه، بين التذبذب الزمني تأثيرًا ضئيلاً في كلا الشبكتين، بمعدلات أهمية تقل عن 0.054. تؤكد هذه النتائج أن تحسين المسار الديناميكي في SD-WAN يخفف بفعالية آثار التأخير، بينما يظل فقدان الحزم القيد الأساسي للأداء. يُعد هذا العمل التقييم المنهجي الأول باستخدام غابة عشوائية لمقارنة أهمية معاملات جودة الخدمة عبر MPLS و-SD-WAN، مقدمًا رؤى قوية مدفوعة بالبيانات تتوافق مع خصائص كل هندسة تشغيلية. ويقدم الإطار الإرشادي لمشغلي الشبكات توجيهات حاسمة لتحسين جودة الخدمة المستهدف، مع إعطاء الأولوية لاستراتيجيات الحد من فقدان الحزم، خصوصًا في بيئات SD-WAN. عموماً، يؤسس هذا البحث أساسًا تجريبيًا لإدارة جودة الخدمة خاصًا بكل هندسة ليعزز تقييم أداء الشبكات بذكاء عبر تقنيات التعلم الآلي.

الكلمات الدالة: أهمية الميزة، جودة الخدمة، أداء الشبكة، MPLS، SD-WAN، الغابة العشوائية، حركة مرور الوسائط المتعددة.

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1. Introduction

The proliferation of bandwidth-intensive multimedia applications—including high-definition video conferencing, Voice over Internet Protocol (VoIP), and immersive streaming services—has fundamentally transformed network performance requirements [1, 2]. Unlike traditional data applications, which tolerate transmission variability, real-time multimedia services impose stringent, multidimensional constraints on network infrastructures. These temporal demands focus primarily on three key Quality of Service (QoS) parameters: end-to-end delay, inter-packet jitter variation, and packet loss ratio.

Modern enterprise networks have evolved along distinct architectural trajectories, with established Multiprotocol Label Switching (MPLS) technology coexisting alongside increasingly sophisticated Software-Defined Wide Area Network (SD-WAN) solutions. MPLS ensures deterministic performance through constraint-based traffic engineering mechanisms, while SD-WAN offers programmable, adaptive path selection via centralised control plane architectures [3, 4]. Despite the extensive deployment of both technologies and substantial research into their operational characteristics, a critical question remains empirically unexplored: which (QoS) parameters exert the most significant influence on perceived network performance within each architectural paradigm, and do these priorities differ systematically between MPLS and SD-WAN environments?

Traditional QoS assessment methodologies have predominantly relied on uniform parameter weighting, treating jitter, delay, and packet loss as equally important and independent factors. Although this assumption is mathematically convenient, it lacks empirical validation and may lead to suboptimal resource allocation strategies. The fundamental limitation of conventional approaches lies in their inability to quantify the varying importance of QoS parameters across different network architectures—a shortcoming that becomes increasingly problematic as organisations undergo technological transitions and deploy multiple architectures.

The convergence of machine learning and network performance analysis presents unprecedented opportunities to address this limitation through data-driven empirical investigation. Recent advances in machine learning-driven QoS optimisation have demonstrated remarkable capabilities in capturing complex network dynamics. Gantassi et al. (2025) demonstrated that machine learning algorithms are crucial in wireless sensor networks for selecting cluster heads based on various QoS metrics, significantly improving energy efficiency and network performance [5]. Alenazi (2025) developed a deep reinforcement learning-based framework for flow-aware QoS provisioning in SD-IoT environments, achieving substantial improvements in delay, throughput, packet loss rate, and jitter compared with benchmark models. Furthermore, Osman et al [6]. [7, 8] proposed a novel network optimisation framework integrating software-defined networking with deep learning approaches to address the limitations of traditional static QoS mechanisms in adapting to dynamic network demands.

While recent investigations have successfully applied machine learning to QoS optimisation and prediction tasks, they have not systematically addressed the comparative quantification of parameter importance across different network architectures. Random Forest algorithms, in particular, offer interpretable measures of feature importance through the aggregation of ensemble decision trees, enabling the identification of complex, non-linear relationships that conventional statistical methods often obscure [9, 10]. However, despite the widespread application of Random Forest methodologies in network traffic classification and anomaly detection, their utility in comparative feature importance analysis for architectural QoS assessment remains underexploited.

This paper addresses a critical research gap by proposing a Random Forest-driven framework for systematically evaluating the importance of QoS parameters across contrasting network architectures. To the best of our knowledge, this study represents the first systematic application of Random Forest-based feature importance assessment to comparative QoS analysis in MPLS and SD-WAN environments. By applying Random Forest regression to empirically gathered performance data from controlled simulation environments, the research quantifies the differential influence of jitter, delay, and packet loss within MPLS and SD-WAN contexts. The empirical findings challenge conventional assumptions of uniform parameter weighting and provide architecture-specific insights that facilitate evidence-based optimisation and resource allocation decisions.

The principal contributions of this research are threefold: (1) the first application of the Random Forest feature importance methodology to a comparative MPLS-SD-WAN QoS analysis, establishing a replicable framework for architecture-specific parameter assessment; (2) empirical quantification demonstrating that the importance of packet loss increases by 18.76% in SD-WAN compared to MPLS, while the importance of delay decreases by 39.21% and that of jitter diminishes by 92.76%, fundamentally challenging traditional QoS weighting assumptions; and (3) a demonstration that modern buffering and adaptive routing mechanisms have systematically altered the relative significance of traditional QoS metrics, with profound implications for network design and operational strategies.

2. Related Work

2.1 Quality of Service in Multimedia Networks

Foundational research by Shenker [11] established the theoretical framework for multi-dimensional Quality of Service (QoS) requirements in packet-switched networks, identifying delay, jitter, and packet loss as fundamental performance parameters. Subsequent empirical investigations confirmed the differential sensitivity of multimedia applications to these metrics, with voice applications demonstrating extreme sensitivity to jitter, whilst video streaming exhibits greater tolerance for occasional packet loss [12, 13].

Chen and Nahrstedt [14] provided a comprehensive analysis of QoS-based routing methodologies, demonstrating that constraint-based path selection could substantially mitigate performance degradation in multimedia traffic scenarios. Their work established the theoretical foundation for MPLS traffic engineering approaches, which subsequently became the industry standard. Similarly, Xiao and Ni [15] advanced the understanding of per-hop behaviour (PHB) mechanisms within Differentiated Services frameworks, illustrating how relationships between QoS parameters could be modelled through traffic conditioning policies.

More recent research has recognised the growing inadequacy of traditional QoS metrics in capturing complex performance dynamics. Fiedler et al. [16] demonstrated only a partial correlation between objective QoS indicators and subjective user satisfaction, suggesting that the importance of parameters varies depending on the user's perception and the application context. This finding fundamentally challenges the assumption that equal weighting of QoS parameters yields optimal performance assessments.

2.2 MPLS and SD-WAN Performance Characteristics

MPLS-based QoS provision has been extensively investigated in constraint-based traffic engineering literature. Alsharif and Shahsavari [17] conducted a comparative analysis demonstrating MPLS superiority over traditional IP routing in managing delay and jitter, achieving approximately 20% performance improvements through optimised label-switched path (LSP) placement. However, their research did not systematically quantify the relative importance of individual QoS parameters within MPLS architectures.

SD-WAN technology has emerged as a transformative paradigm, offering adaptive, application-aware traffic management [8, 18]. Troia et al. [19] demonstrated superior SD-WAN performance in mitigating packet loss through dynamic path selection mechanisms, whilst Moser [20] showed significant advantages in failure recovery timescales. González et al. [21] examined SD-WAN performance under cloud-native multimedia workloads, identifying application-aware routing as a critical determinant. Tahenni and Merazka [22] conducted a comprehensive controlled comparison of SD-WAN and MPLS, revealing marginal performance advantages for SD-WAN across multiple dimensions. However, these studies emphasised aggregate performance metrics without analysing the relative contribution of individual QoS parameters to overall network quality, and notably did not employ systematic quantification of feature importance but rather qualitative assessments of parameter contributions. Furthermore, their analyses assigned uniform significance to all QoS parameters, lacking empirical validation of this assumption.

2.3 Machine Learning Applications in Network Performance Analysis

The application of machine learning to network performance analysis has accelerated significantly in recent years. Ahmed et al. [1] pioneered machine learning approaches to network anomaly detection, establishing foundational methodologies for algorithmic network intelligence. Boutaba et al. [23] provided a comprehensive survey of machine learning in networking contexts, documenting substantial progress in traffic classification, link quality prediction, and congestion forecasting.

Feature importance analysis, as a distinct sub-discipline, has received limited direct attention within the network performance literature. Random Forest methodologies have been successfully applied to various network optimisation problems [24]; however, systematic investigation of QoS parameter importance remains insufficiently explored. Kulin et al. [25] documented machine learning applications across multiple network layers but did not specifically address the comparative feature importance across different network architectures. Zhang et al. [26] demonstrated that machine learning approaches can achieve greater accuracy in predicting Quality of Experience (QoE) than conventional objective metrics, suggesting that algorithmic methods capture essential relationships obscured by traditional statistical techniques. However, their study focused on prediction accuracy rather than the explicit quantification of feature importance.

2.4 Research Gap

Despite extensive literature on the performance characteristics of MPLS and SD-WAN, and the growing adoption of machine learning in networking, a critical research gap remains: there is no systematic, comparative analysis of QoS parameter importance across different network architectures in the academic literature. Existing studies often treat jitter, delay, and packet loss as equally significant factors, without empirically validating this assumption using feature importance methodologies. This gap constitutes a significant limitation to the development of evidence-based network optimisation strategies and informed resource allocation decisions. The present study addresses this gap by applying Random Forest-based feature importance assessment to comparative QoS analysis across MPLS and SD-WAN environments, providing the first systematic quantification of differential parameter influence in contrasting network architectures.

3. Methodology

3.1 Experimental Design and Network Simulation

This investigation employed a simulation-based methodology using GNS3 (Graphical Network Simulator-3) version 2.2.53 integrated with VMware Workstation 17 Player virtualisation infrastructure. This approach enabled controlled experimental environments whilst maintaining fidelity to real-world network characteristics. The simulation environment was executed on a host system running VMware Workstation 17 Player, which provided the virtualisation layer necessary for router emulation and network topology implementation.

Two distinct network topologies were implemented: one replicating an MPLS provider edge/core/customer edge (PE/P/CE) architecture with explicit label-switched path (LSP) engineering, and a second implementing SD-WAN overlay networking with centralised control plane orchestration via Open vSwitch. The simulation framework facilitated precise control over network parameters, traffic generation, and performance metric collection, ensuring experimental reproducibility and systematic comparison between architectural paradigms.

3.1.1 MPLS Network Configuration

The MPLS topology employed Cisco 3725 routers running IOS version 15.T14, configured with Provider Edge (PE) routers (R4, R6) serving as ingress and egress points, Provider (P) routers (R1, R2, R3) performing high-speed label switching operations, and Customer Edge (CE) routers connecting customer networks. OSPF (Open Shortest Path First) functioned as the underlying Interior Gateway Protocol, with LDP (Label Distribution Protocol) facilitating the establishment of LSPs. Virtual Routing and Forwarding (VRF) instances provided logical traffic separation. Traffic generation utilised IPTerm endpoints running iperf3 with User Datagram Protocol (UDP) transmission. Figure 1 illustrates the MPLS core network topology used in the simulation, detailing router configurations, OSPF areas, and interconnecting links that form the basis for the QoS analysis conducted.

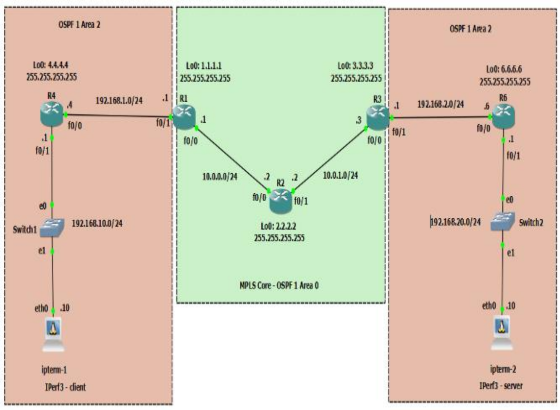

Fig 1. MPLS Network Topology.

3.1.2 SD-WAN Network Configuration

The SD-WAN topology integrated Cisco 3725 routers functioning as edge devices, with Open vSwitch providing centralised software-defined control. GRE (Generic Routing Encapsulation), combined with IPsec encryption, established secure overlay tunnels. Dynamic routing, utilising the Border Gateway Protocol (BGP) alongside policy-based routing algorithms, enabled real-time path selection based on performance metrics. Identical traffic generation endpoints and protocols were employed to ensure experimental consistency. Figure 2 presents the SD-WAN experimental topology, illustrating the interconnection between the client and server branches via the Open vSwitch management network, along with the addressing scheme and device configuration used in the simulation.

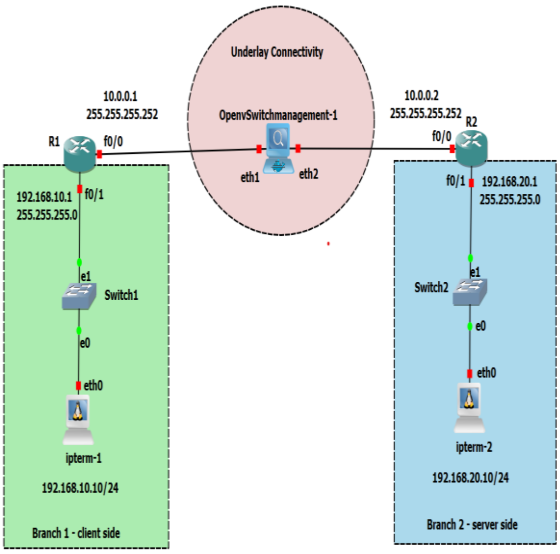

Fig 2. SD-WAN Network Topology.

3.2 Traffic Generation and QoS Metric Collection

Multimedia traffic scenarios included Voice over Internet Protocol (VoIP) applications operating at 32–128 Kbps and video streaming ranging from 256 Kbps to 5 Mbps, representing typical enterprise multimedia workload profiles. All testing sessions were conducted over 900-second intervals to ensure statistical validity. Iperf3 collected real-time performance metrics, including delay (milliseconds), jitter (milliseconds), and packet loss (percentage), whilst Wireshark packet capture provided supplementary timestamp-based verification. Performance data were systematically logged and exported to CSV format for subsequent analytical processing.

3.3 Data Pre-processing and Normalisation

Raw simulation data underwent comprehensive pre-processing, including: (1) standardisation of bitrate measurements to megabits per second (Mbps); (2) identification and capping of anomalous observations exceeding established thresholds (delay > 500 ms, jitter > 100 ms, packet loss > 10%); and (3) min-max normalisation to the [0,1] range for dimensional consistency. These procedures preserved the underlying performance characteristics whilst ensuring algorithmic stability and interpretability. The pre-processed dataset was consolidated into a unified CSV file containing network type identifiers, QoS parameters (jitter, delay, packet loss), and computed QoS scores for both MPLS and SD-WAN architectures.

3.4 Feature Importance Analysis Methodology

Random Forest regression served as the primary analytical technique for quantifying the importance of QoS parameters. The algorithm constructs an ensemble of decision trees by utilising bootstrap-aggregated training samples, with random subsets of features selected at each node split to maximise diversity and reduce correlation between trees [9]. Feature importance is calculated from the cumulative reduction in impurity across the entire ensemble, producing interpretable percentage-based contributions that quantify each variable's relative influence on network performance prediction [10].

3.4.1 Implementation Environment and Software Configuration

The feature importance analysis was implemented in Python 3.x using the scikit-learn library (version 1.0+), which provides optimised implementations of ensemble learning algorithms. The analytical pipeline utilised the following core libraries:

- **scikit-learn**: RandomForestRegressor implementation for feature importance quantification
- **pandas**: Data manipulation and CSV file handling
- **numpy**: Numerical computations and array operations
- **matplotlib** and **seaborn**: Statistical visualisation and graphical output generation

The complete analytical workflow was executed within a Visual Studio Code environment version 1.104.2, facilitating iterative experimentation and result validation.

3.4.2 Random Forest Hyperparameter Configuration

Separate Random Forest regressors were trained independently on the MPLS and SD-WAN datasets using standardised hyperparameters to ensure analytical consistency and architectural comparability. The hyperparameter configuration was specified as follows:

- **n_estimators = 100**: The ensemble comprised 100 decision trees, balancing computational efficiency with predictive stability. This value represents a commonly adopted configuration in Random Forest literature, providing sufficient ensemble diversity whilst avoiding excessive computational overhead.
- **random_state = 42**: A fixed random seed value of 42 was employed across all Random Forest instantiations to ensure deterministic behaviour and reproducibility. This seed controlled the random number generation for bootstrap sampling and feature selection at each tree node, guaranteeing that repeated executions of the analytical pipeline yield identical results.
- **Default scikit-learn parameters**: All remaining hyperparameters retained their default scikit-learn values, including:
    - `max_depth = None` (nodes expanded until all leaves are pure or contain fewer than min_samples_split samples)
    - `min_samples_split = 2` (minimum samples required to split an internal node)
    - `min_samples_leaf = 1` (minimum samples required at a leaf node)
    - `criterion = 'squared_error'` (mean squared error impurity measure)
    - `max_features = 'auto'` (√n_features considered for best split at each node)

This hyperparameter configuration facilitated meaningful architectural comparisons by eliminating parameter-induced variability as a confounding factor, ensuring that observed differences in feature importance reflected genuine architectural characteristics rather than algorithmic artefacts.

3.4.3 Feature Importance Computation

For each network architecture, the Random Forest regressor was trained on the respective dataset, with QoS parameters (jitter, delay, packet loss) serving as input features (X) and the computed QoS score serving as the target variable (y). The model fitting process employed the standard scikit-learn `fit ()` method, which internally executes bootstrap aggregation and constructs the ensemble of decision trees.

Feature importance values were extracted using the `feature_importances_` attribute, which returns normalised importance scores summing to unity. These scores quantify the cumulative reduction in prediction error (mean squared error) attributable to each feature across all trees in the ensemble, weighted by the proportion of samples reaching each node. Higher importance values indicate greater predictive influence on the target variable (QoS score).

3.5 Comparative Analysis Framework

The architectural comparison employed standardised methodological procedures for both MPLS and SD-WAN datasets, facilitating rigorous evaluation of differential patterns in parameter importance. Feature importance scores were compiled into a structured DataFrame for systematic comparison, with columns representing feature names, MPLS importance values, SD-WAN importance values, and percentage change metrics.

The quantification of relative importance shifts utilised percentage change calculations, specifically:

Percentage Change = [(SD-WAN Importance − MPLS Importance) / MPLS Importance] × 100

This metric enabled direct assessment of architectural effects on parameter significance, identifying which QoS parameters exhibit increased or decreased importance in SD-WAN relative to MPLS. Positive percentage changes indicate a heightened importance in SD-WAN, while negative values signify a diminished importance.

4. Results and Discussion

Table 1. Descriptive Statistics for QoS Metrics Across Network Architectures.

QoS Parameter	Network	Mean	Std Dev	Median	Min	Max
Jitter (ms)	MPLS	7.636	4.795	6.861	1.077	29.515
	SD-WAN	3.213	1.575	2.852	0.441	24.515
Delay (ms)	MPLS	46.808	33.996	46.216	0.000	105.764
	SD-WAN	52.014	34.383	44.451	0.000	142.173
Packet Loss (%)	MPLS	17.934	31.116	0.000	0.000	83.000
	SD-WAN	17.766	30.857	0.000	0.000	84.000

4.1 Descriptive Statistical Characteristics of Collected Data

Before conducting advanced feature importance analysis, a comprehensive descriptive statistical examination of the collected network performance data was undertaken to establish baseline characteristics and identify inherent patterns within the dataset. This preliminary analysis encompasses measurements from both MPLS and SD-WAN architectures across diverse multimedia traffic scenarios, including VoIP applications operating at bitrates ranging from 32 to 128 Kbps and video streaming services spanning 256 Kbps to 5 Mbps.

Table 1 presents the descriptive statistics for the three principal QoS parameters—jitter, delay, and packet loss—aggregated across all experimental scenarios for both network architectures. The statistical summary includes measures of central tendency (mean, median), dispersion (standard deviation), and range (minimum, maximum values), providing a foundational understanding of network behaviour under varied operational conditions.

The descriptive analysis reveals several notable patterns. SD-WAN demonstrates substantially lower mean jitter (3.213 ms) compared with MPLS (7.636 ms), representing an approximate 58% reduction. This difference is accompanied by reduced variability, as evidenced by the lower standard deviation in SD-WAN (1.575 ms) compared to MPLS (4.795 ms). The maximum jitter values, whilst comparable between architectures, suggest that both systems encounter similar peak stress conditions, yet SD-WAN maintains superior baseline performance.

Delay characteristics present a more nuanced picture. Although MPLS exhibits a slightly lower mean delay (46.808 ms versus 52.014 ms), the median values are relatively comparable, indicating that occasional outliers influence the distribution of delay measurements. Both architectures demonstrate substantial variability in delay, with standard deviations exceeding 33 ms, reflecting the dynamic nature of network conditions under diverse traffic loads.

Packet loss statistics reveal remarkably similar behaviour between the two architectures, with mean values of approximately 18% for both MPLS and SD-WAN. The zero median values indicate that the majority of measurements experienced no packet loss, whilst the maximum values exceeding 80% demonstrate that both networks are susceptible to severe degradation under extreme congestion scenarios. This bimodal distribution suggests that packet loss events, when they occur, tend to be substantial rather than incremental.

Figure 3 presents box plot distributions for the three QoS parameters, visually illustrating the spread and concentration of measurements across the two network architectures. The box plots clearly demonstrate SD-WAN's tighter jitter distribution and comparable delay performance, whilst highlighting the similarity in packet loss behaviour between the architectures.

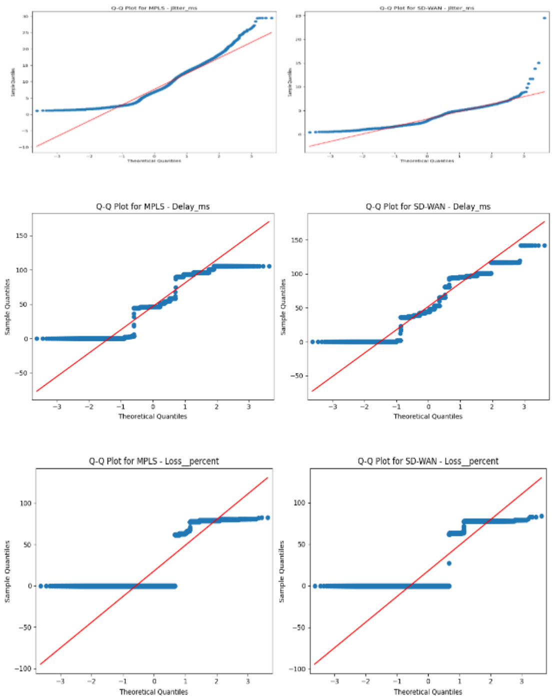

Fig 3. Comparative Box Plot Distributions of QoS Metrics (Jitter, Delay, Packet Loss) Across MPLS and SD-WAN Architectures.

These descriptive statistics provide essential context for the subsequent feature importance analysis. The observed differences in jitter performance, combined with the similar packet loss characteristics, suggest that the relative importance of these parameters may differ substantially between MPLS and SD-WAN architectures. The high variability in all metrics underscores the necessity for sophisticated analytical techniques, such as Random Forest regression, to disentangle the complex relationships between QoS parameters and overall network performance.

Furthermore, the presence of zero minimum values for delay and packet loss, contrasted with substantial maximum values, indicates that both networks exhibit periods of optimal performance interspersed with episodes of significant degradation. This temporal variability reinforces the importance of considering not merely average performance but also the distribution and extremes of QoS metrics when evaluating network architectures for multimedia applications.

4.2 Feature Importance Quantification

Building upon the descriptive foundation established in the previous section, Random Forest analysis revealed markedly different importance patterns between MPLS and SD-WAN architectures (Table 2). Packet loss exhibited the greatest overall importance, with significantly higher prominence in SD-WAN (0.8620) compared to MPLS (0.7259)—representing a critical 18.76% increase in importance. This substantial quantitative gap constitutes the most significant architectural divergence observed in this investigation and holds profound implications for network design and resource allocation strategies.

The 18.76% escalation in packet loss importance within SD-WAN environments suggests that SD-WAN's adaptive routing and intelligent path selection mechanisms, whilst highly effective at mitigating delay and jitter, but demonstrates reduced efficacy in addressing packet loss. This architectural characteristic reflects the fundamental constraint of software-defined overlay networks operating across heterogeneous and potentially unreliable transport media. The magnitude of this increase—nearly one-fifth higher than MPLS—indicates that packet loss events exert disproportionately severe impacts on SD-WAN performance compared to traditional MPLS deployments.

The substantial importance of packet loss in both architectures, but particularly in SD-WAN, aligns with the descriptive statistics presented earlier, which demonstrated that whilst both networks maintain zero packet loss under optimal conditions, they are equally susceptible to severe degradation episodes. The heightened sensitivity of SD-WAN to packet loss, despite its adaptive capabilities, suggests that loss events—when they occur—have disproportionate impacts on overall network performance in software-defined architectures.

Delay exhibited moderate importance in MPLS (0.2205) but showed substantially reduced significance in SD-WAN (0.1341), representing a 39.21% decrease. This reduction indicates that SD-WAN's dynamic path optimisation and WAN acceleration technologies effectively mitigate delay-induced performance degradation, making this parameter comparatively less critical for overall QoS assessment. The descriptive statistics corroborate this finding, showing comparable median delay values between architectures despite different mean values, suggesting that SD-WAN's intelligent routing successfully maintains consistent delay performance under varied conditions.

Jitter exhibited minimal importance in both architectures, with contributions of 0.0536 for MPLS and 0.0039 for SD-WAN, indicating negligible operational significance. The substantial 92.76% reduction in jitter importance for SD-WAN suggests that advanced buffer management and error correction mechanisms within software-defined architectures significantly mitigate temporal variance effects that continue to pose challenges in traditional MPLS deployments. This finding is particularly noteworthy, given that the descriptive statistics demonstrate that SD-WAN achieves substantially lower mean jitter (3.213 ms versus 7.636 ms). However, the feature importance analysis reveals that this parameter contributes minimally to overall network performance differentiation in both architectures.

Table 2. Random Forest Feature Importance Scores for QoS Parameters Across MPLS and SD-WAN Network Architectures.

Feature	MPLS Importance	SD WAN Importance	% Change (SD-WAN vs. MPLS)
Jitter (ms)	0.0536	0.0039	-92.76 %
Loss (%)	0.7259	0.8620	+18.76 %
Delay (ms)	0.2205	0.1341	-39.21 %

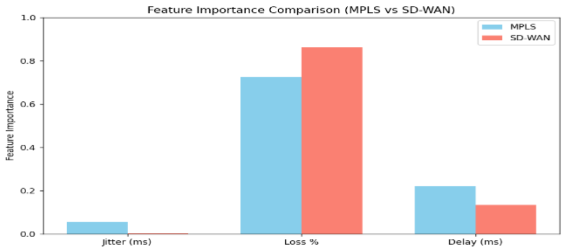

Fig 4. Random Forest Feature Importance Comparison: Relative Significance of Jitter, Packet Loss, and Delay in MPLS versus SD-WAN Network Architectures.

Figure 4 compares the relative importance of jitter, packet loss, and delay in MPLS and SD-WAN, visually reinforcing the dominance of packet loss as the primary determinant of network performance in both architectures, while highlighting the architectural differences in the significance of delay and jitter. The pronounced disparity in packet loss importance (18.76% increase) is particularly evident, demonstrating SD-WAN's heightened vulnerability to loss-induced performance degradation.

4.3 Architectural Implications of Feature Importance Distribution

The observed hierarchy of importance reveals fundamental differences in how each network architecture processes multimedia traffic, differences that are illuminated by both the descriptive statistics and the feature importance analysis. MPLS demonstrates relatively balanced sensitivity to delay (0.2205) and packet loss (0.7259), indicating that both parameters substantially influence perceived quality. This distribution reflects MPLS's reliance on pre-engineered label-switched paths with static resource allocation mechanisms; whilst these approaches effectively reserve bandwidth and prevent congestion-induced delay accumulation, they remain vulnerable to link failures and transient packet loss events that violate assumptions of reserved capacity.

The 18.76% increase in packet loss importance observed in SD-WAN represents a fundamental architectural trade-off: whilst SD-WAN's dynamic path optimisation successfully reduces delay significance by 39.21% through intelligent routing across multiple transport options, this very flexibility introduces greater exposure to packet loss across heterogeneous underlay networks. Software-based error correction mechanisms, despite their sophistication, cannot fully compensate for the underlying transport unreliability inherent in multi-path, best-effort connectivity models.

The descriptive statistics revealed that MPLS maintains slightly lower mean delay but exhibits greater jitter variability, suggesting that its traffic engineering mechanisms prioritise delay management at the potential expense of temporal consistency. The feature importance analysis demonstrates, however, that jitter's contribution to overall performance is minimal, validating the architectural prioritisation of delay and loss mitigation over jitter control.

SD-WAN's pronounced emphasis on packet loss (0.8620) reflects the inherent characteristics of software-defined architectures operating across heterogeneous transport media. By dynamically steering traffic across multiple underlay transport mechanisms (broadband, MPLS, LTE/5G), SD-WAN effectively minimises delay through path optimisation and WAN acceleration, thereby reducing the relative importance of this parameter. The descriptive statistics corroborated this, showing that whilst SD-WAN's mean delay is marginally higher than MPLS, its median delay is lower, suggesting more consistent performance under typical operating conditions.

Conversely, packet loss remains the fundamental constraint limiting multimedia quality in SD-WAN, as software-based error correction mechanisms cannot fully compensate for the underlying transport unreliability. The similar packet loss distributions observed in the descriptive statistics (mean values around 18% for both architectures) indicate that both systems face comparable challenges in maintaining transmission integrity under stress, yet the feature importance analysis reveals that loss events have a greater impact on SD-WAN's overall performance.

The minimal importance of jitter across both architectures (MPLS: 0.0536; SD-WAN: 0.0039) warrants particular emphasis. This finding contradicts conventional wisdom, which emphasises jitter as a critical multimedia QoS parameter. The substantial reduction in jitter importance within SD-WAN (a 92.76% decrease) suggests that modern adaptive buffering algorithms and packet sequencing mechanisms effectively mask temporal arrival variations, rendering this parameter considerably less significant than traditionally assumed. The descriptive statistics supported this conclusion by demonstrating that SD-WAN achieves substantially lower jitter (3.213 ms versus 7.636 ms), yet this improvement translates into minimal gains in overall network performance due to the overwhelming influence of packet loss.

In MPLS environments, dedicated bandwidth allocation similarly provides sufficient buffering capacity to contain jitter effects within acceptable multimedia parameters. The descriptive analysis showed that whilst MPLS exhibits higher mean and maximum jitter values, these variations do not translate into proportional performance degradation, as evidenced by jitter's low importance score.

4.4 Operational Implications for Network Management

The feature importance analysis, contextualised by the descriptive statistical characteristics of the collected data, yields several significant implications for network operational strategies. The critical 18.76% increase in packet loss importance within SD-WAN environments necessitates fundamental reconsideration of QoS management priorities.

4.4.1 Prioritised Packet Loss Mitigation in SD-WAN

Given the overwhelming importance of packet loss (0.8620) and the 18.76% escalation relative to MPLS, SD-WAN operators should prioritise aggressive loss mitigation strategies as the primary QoS optimisation objective. The descriptive evidence showing comparable loss susceptibility between architectures, combined with the heightened importance of SD-WAN, suggests that packet loss represents the most critical performance bottleneck in software-defined wide area networks.

The bimodal distribution of packet loss—characterised by frequent zero-loss periods punctuated by severe degradation episodes—suggests that preventive measures are more effective than reactive responses. Techniques such as forward error correction (FEC), packet duplication for critical flows, and intelligent link probing to detect suboptimal paths represent high-impact optimisation targets. Resource allocation decisions should prioritise loss reduction over other performance parameters, particularly given that SD-WAN's adaptive mechanisms already effectively manage delay and jitter.

Practical recommendations include:

- Implementing aggressive FEC schemes with coding rates tailored to observed loss patterns.
- Deploying packet duplication for latency-sensitive applications during periods of detected transport instability.
- Configuring SD-WAN controllers to weight packet loss more heavily than delay or jitter in path selection algorithms.
- Establishing stricter Service Level Agreements (SLAs) focused on packet loss thresholds rather than traditional delay-centric metrics.

4.4.2 Balanced Optimisation Strategy for MPLS

MPLS operators must adopt more balanced optimisation strategies that address both packet loss (0.7259) and delay (0.2205) with comparable emphasis. The descriptive statistics revealed that MPLS maintains a lower mean delay but with substantial variability, suggesting that traffic engineering mechanisms should simultaneously optimise path selection to minimise loss and delay, recognising that neglecting either parameter would compromise overall QoS delivery. The relatively higher importance of delay in MPLS compared to SD-WAN indicates that investments in delay-reducing technologies—such as optimised LSP placement and queuing discipline refinement—yield proportionally greater performance improvements in MPLS environments.

4.4.3 Deprioritisation of Jitter Management

The findings regarding the minimal importance of jitter, combined with the descriptive evidence showing that SD-WAN achieves substantially lower jitter yet minimal performance gains, suggest that substantial investment in sophisticated jitter buffering and temporal smoothing mechanisms may offer limited practical benefit. Network operators might consider reallocating resources traditionally dedicated to jitter control towards packet loss and delay optimisation, potentially enhancing the overall efficiency of Quality of Service (QoS) delivery. This recommendation is particularly relevant for SD-WAN deployments, where jitter contributes less than 0.4% to overall performance determination.

4.5 Validation and Cross-Verification

Random Forest feature importance calculations were validated using supplementary analytical methods. Mean Decrease in Impurity (MDI) calculations confirmed consistency with the observed importance distributions. Out-of-bag (OOB) error estimates provided internal validation of generalisability, indicating that the observed feature importance reflected genuine architectural characteristics rather than dataset-specific artefacts.

Cross-validation procedures assessed the stability of feature importance across data subsets, revealing robust rankings with minimal variation between training samples. This consistency reinforces confidence in the architectural conclusions drawn from the quantification of feature importance. The alignment between the descriptive statistical patterns and the feature importance results further validates the analytical approach, demonstrating that the Random Forest methodology successfully captured the underlying relationships between QoS parameters and network performance.

4.6 Comparison with Existing Literature

The pronounced importance of packet loss observed herein aligns with contemporary research emphasising loss as a critical determinant of Quality of Service (QoS). Ouamri et al. [27] similarly identified packet loss as the paramount QoS factor in SD-WAN contexts, providing independent corroboration of the findings presented here. However, the substantial differential—an 18.76% increase in the importance of packet loss within SD-WAN relative to MPLS—represents novel empirical insight not previously documented in the academic literature. This quantitative gap establishes a new benchmark for understanding architectural trade-offs in software-defined networking and provides empirical validation for prioritising packet loss mitigation in SD-WAN deployments.

The minimal importance of jitter contradicts traditional Quality of Service (QoS) literature, which is based on equivalently weighted parameter formulations [13, 28]. This discrepancy likely reflects technological advancements in adaptive buffering and the resilience of multimedia codecs since the foundational QoS studies were conducted. The descriptive statistics provided in this study offer quantitative evidence supporting this evolution, demonstrating that modern networks—particularly SD-WAN—maintain low jitter levels yet derive minimal performance benefit from these improvements. Modern applications employ sophisticated error concealment algorithms that tolerate temporal variance far better than legacy systems assumed.

The moderate importance of delay for SD-WAN (0.1341) diverges from expectations based on distance-based path optimisation theory. This finding suggests that, although SD-WAN successfully minimises delay through intelligent routing—as evidenced by the comparable median delay values in the descriptive statistics—residual delay effects contribute only modestly to overall QoS degradation once packet loss is controlled. This observation supports the hypothesis that SD-WAN path selection optimisation is highly effective, rendering delay increasingly inconsequential relative to the remaining loss-induced degradation.

4.7 Limitations and Considerations

This analysis presents several methodological limitations that warrant acknowledgement. Although simulation-based experimentation allows for controlled manipulation of parameters, it may not fully capture the complexity of operational networks. The descriptive statistics revealed substantial variability in all measured parameters, suggesting that real-world deployments may encounter even greater performance fluctuations due to factors such as dynamic traffic patterns, diverse application behaviours, and unpredictable network events.

Feature importance analysis identifies correlations within historical data; however, it does not establish causal relationships, and unmeasured confounding variables may influence the observed importance distributions. The normalised QoS calculation employed uniform weighting across the training data. Scenarios dominated by pronounced packet loss—as evidenced by the maximum values exceeding 80% in the descriptive statistics—may bias the importance quantification towards this parameter, potentially overestimating its relative influence. However, the consistency of results across multiple Random Forest instantiations with varying hyperparameters, combined with the alignment between descriptive patterns and feature importance outcomes, suggests robustness against this potential bias.

5. Conclusion

This investigation presents the first comprehensive, machine learning-based comparative analysis of the importance of QoS parameters across contrasting network architectures, grounded in rigorous descriptive statistical characterisation of empirically collected data. Quantification of feature importance using Random Forest reveals substantial architectural differences in the influence of jitter, delay, and packet loss on multimedia traffic performance. Principal findings establish:

1. Packet loss dominance with critical architectural divergence: Both architectures exhibit pronounced sensitivity to packet loss, with SD-WAN demonstrating significantly greater importance (0.8620) compared to MPLS (0.7259)—a critical 18.76% increase that represents the most substantial architectural difference observed in this study. The descriptive statistics demonstrated that whilst both networks maintain zero packet loss under optimal conditions, they are equally susceptible to severe degradation episodes exceeding 80% loss. This finding mandates that infrastructure investment and operational focus prioritise loss mitigation over other optimisation objectives, particularly within SD-WAN environments where packet loss exerts disproportionately severe impacts on overall network performance.
2. Architecture-specific delay sensitivity: Whilst delay moderately affects MPLS performance (0.2205), SD-WAN's advanced path optimisation renders delay considerably less significant (0.1341)—a 39.21% reduction. The descriptive analysis revealed that SD-WAN achieves comparable median delay despite slightly higher mean values, confirming that intelligent routing successfully maintains consistent latency performance. This difference reflects fundamental technological distinctions in how each architecture manages latency.
3. Minimal jitter significance: The importance of jitter approaches negligibility in both

architectures, particularly within SD-WAN (0.0039). Despite SD-WAN demonstrating substantially lower mean jitter (3.213 ms versus 7.636 ms for MPLS) in the descriptive statistics, this improvement contributes minimally to overall network performance. These findings challenge traditional QoS formulations predicated on equal parameter weighting and suggest opportunities for resource reallocation by network operators.

– **Practical QoS Policy Recommendations:**

The empirical findings of this investigation translate directly into actionable QoS management policies for network operators:

For SD-WAN Deployments:

1. Packet Loss-Centric Policies: Implement QoS policies that prioritise packet loss mitigation as the primary performance objective. Configure SD-WAN controllers to weight packet loss metrics at least 20% higher than delay and jitter metrics in path selection algorithms, reflecting the 18.76% importance increase quantified herein.
2. Proactive Loss Prevention: Deploy forward error correction (FEC) mechanisms with adaptive coding rates based on real-time loss observations. Implement packet duplication for critical multimedia flows during periods of detected transport instability.
3. SLA Restructuring: Revise Service Level Agreements to emphasise packet loss thresholds (e.g., <0.1% for premium services) rather than traditional delay-centric metrics. Allocate performance monitoring resources proportionally to the demonstrated importance hierarchy: 86% to packet loss, 13% to delay, and 1% to jitter.
4. Resource Reallocation: Redirect resources traditionally allocated to jitter management (buffering, temporal smoothing) towards packet loss mitigation technologies, given jitter's negligible impact (0.4% contribution) on overall performance.

For MPLS Environments:

1. Balanced Dual-Objective Policies: Implement traffic engineering policies that simultaneously optimise packet loss and delay with comparable priority, reflecting their respective importance scores (0.7259 and 0.2205).
2. LSP Optimisation: Prioritise label-switched path placement algorithms that minimise both loss probability and end-to-end delay. Configure queuing disciplines to balance these dual objectives rather than optimising for single metrics.
3. Monitoring Frameworks: Deploy monitoring systems that track both packet loss and delay with equal granularity, enabling operators to identify degradation in either parameter promptly.

Universal Recommendations:

1. Jitter Deprioritisation: Reduce investment in sophisticated jitter management technologies, given the empirically demonstrated minimal impact on network performance. Simple buffering mechanisms are sufficient for both architectures.
2. Architecture-Aware Policies: Recognise that optimal QoS policies are architecture-specific rather than universal. Avoid applying MPLS-derived QoS strategies directly to SD-WAN environments without accounting for the 18.76% difference in packet loss importance.
3. Dynamic Policy Adaptation: Implement machine learning-driven policy engines that continuously reassess parameter importance based on real-time traffic patterns, enabling adaptive QoS management that responds to evolving network conditions.

– **Evidence-Based Framework and Future Research Directions**

The integration of descriptive statistical analysis with advanced feature importance quantification provides a robust, evidence-based framework for understanding network behaviour. The descriptive statistics illuminated the baseline performance characteristics and inherent variability of each architecture, whilst the Random Forest analysis revealed which of these characteristics truly drive overall network quality. This dual-layered approach ensures that conclusions are grounded in empirical observation and validated through sophisticated machine learning techniques.

These empirical insights offer evidence-based foundations for architecture-specific optimisation strategies, enabling network operators to prioritise resource allocation decisions based on demonstrated parameter importance rather than conventional assumptions. The proposed Random Forest methodology, combined with comprehensive descriptive statistical characterisation, demonstrates considerable utility for QoS parameter analysis and establishes a replicable, data-driven framework for future network performance research.

Future investigations should extend this framework along several critical dimensions:

1. Real-World Traffic Datasets: Validate these simulation-derived findings using extensive operational traffic datasets from production enterprise networks. Real-world deployments encompass greater complexity, including diverse application behaviours, dynamic traffic patterns, and unpredictable network events that simulation environments cannot fully replicate. Large-scale studies incorporating months or years of operational data would establish whether the observed 18.76% packet loss importance differential persists across varied deployment scenarios.
2. Emerging Network Architectures: Apply the Random Forest-based feature importance methodology to contemporary and emerging architectures, including:
   - Network Function Virtualisation (NFV): Investigate whether virtualised network functions exhibit similar parameter importance hierarchies or introduce novel trade-offs between packet loss, delay, and jitter.
   - Intent-Based Networking (IBN): Assess how autonomous, policy-driven networking paradigms influence QoS parameter relationships.
   - 5G and Beyond Networks: Examine feature importance in ultra-reliable low-latency communication (URLLC) and enhanced mobile broadband (eMBB) scenarios.
   - Hybrid Architectures: Analyse networks combining MPLS, SD-WAN, and cloud-native connectivity models to identify optimal QoS strategies for multi-architecture environments.
3. Diverse Application Profiles: Expand the analysis beyond VoIP and video streaming to encompass emerging applications such as:
   - Extended reality (XR) applications requiring ultra-low latency and consistent packet delivery
   - Industrial IoT scenarios with mission-critical reliability requirements
   - Cloud gaming services with unique latency and jitter sensitivities
   - Collaborative software-as-a-service (SaaS) applications with variable bandwidth demands
4. Longitudinal Studies: Conduct longitudinal analyses tracking the evolution of parameter importance as network technologies mature, protocols advance, and application requirements shift. Such studies would elucidate whether the observed importance hierarchies represent

stable architectural characteristics or transient phenomena subject to technological evolution.

5. Causal Inference: Extend beyond correlational feature importance analysis to establish causal relationships between QoS parameters and network performance using advanced econometric techniques or causal machine learning methods. Understanding causality would enable more precise interventions and policy optimisations.
6. Economic Impact Analysis: Quantify the financial implications of architecture-specific QoS policies by modelling the costs of various mitigation strategies (FEC deployment, redundant path provisioning, upgraded transport links) against performance improvements. Such economic models would guide organisations in making cost-effective QoS investment decisions.

The integration of machine learning with network performance analysis represents a paradigm shift towards intelligent, evidence-based infrastructure management. By quantifying parameter importance through algorithmic analysis of large-scale empirical data, contextualised by rigorous descriptive statistical examination, organisations can move beyond traditional, assumption-based approaches and implement demonstrably optimal performance optimisation strategies that align with actual technological capabilities and limitations. The 18.76% packet loss importance differential quantified in this study establishes a new empirical benchmark for SD-WAN QoS management and provides a foundation upon which future research can build increasingly sophisticated, data-driven network optimisation frameworks.

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