

# A method for software-defined quantum network state assessment and detection of anomalous or degraded communication channels

Marek Aleksander<sup>1,†</sup>, Yurii Kulakov<sup>2,†</sup>, Alla Deveciogullari<sup>2,\*,†</sup>, Oksana Zhurakovska<sup>2,†</sup>, Olena Havrylenko<sup>2,†</sup> and Dmytro Sytnyk<sup>2,†</sup>

<sup>1</sup>Nowy Sacz School of Business - National Louis University, Grunwaldzka Str., 17, Nowy Sacz, 33-300, Poland

<sup>2</sup>National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Beresteiskyi Ave., 37, Kyiv, 03056, Ukraine

## Abstract

Software-Defined Quantum Networks (SDQNs) are considered a promising foundation for the development of next-generation secure communication infrastructures. The efficient operation of such networks requires continuous monitoring of quantum channel conditions and timely detection of anomalies that may adversely affect the quality of quantum information transmission. Unlike classical networks, where network state assessment methodologies are well established, quantum networks still lack a unified approach for comprehensive network state evaluation and analysis. Existing studies are primarily focused on individual characteristics of quantum channels and do not provide an integrated assessment of their combined impact on overall network performance. This paper proposes a method for assessing the state of a Software-Defined Quantum Network based on a multi-criteria decision-making framework. The assessment is performed using a set of parameters that are critical for ensuring the reliable operation of quantum channels and maintaining the required quality of quantum information transmission. The VIKOR method is employed to evaluate and determine the network state, enabling the ranking of alternatives according to their proximity to a compromise solution while accounting for the conflicting influence of individual parameters on the overall network condition. The proposed approach enables the classification of Software-Defined Quantum Network states, the localization of problematic network segments, and the detection of service quality degradation. The obtained results can be applied to real-time monitoring of quantum networks and decision support within SDQN management systems, particularly for routing and network resource orchestration tasks. The practical significance of the proposed method lies in providing a foundation for intelligent resource management, automated anomaly detection, and enhanced reliability of future quantum communication infrastructures.

## Keywords

SDN, SDQN, quantum channel, cyberattacks, quantum channel state assessment, anomalous channel detection, MCDM methods, VIKOR

## 1. Introduction

Modern computer networks are characterized by a rapid growth in traffic volumes, an increasing number of connected devices, and the emergence of new services with stringent requirements for latency, reliability, and information security. Alongside the development of traditional data communication networks, quantum networks are being actively investigated, offering fundamentally new capabilities for information protection through the use of quantum states and quantum key distribution mechanisms. Under these conditions, Software-Defined Networking (SDN) technologies become particularly important, as they enable centralized management of network resources, dynamic adaptation of network configurations to current operating conditions, and efficient orchestration of heterogeneous infrastructures.

WCH'26: Fifth International Workshop on Cyber Hygiene, June 25–26, 2026, Krakow, Poland

\*Corresponding author.

<sup>†</sup>These authors contributed equally.

✉ aleksandermarek4@gmail.com (M. Aleksander); ya.kulakov@gmail.com (Y. Kulakov); deveciogullari.alla@edu.kpi.ua (A. Deveciogullari); o.zhurakovska@kpi.ua (O. Zhurakovska); gelena1980@gmail.com (O. Havrylenko); sytnyk.d.s.-is34@edu.kpi.ua (D. Sytnyk)

ORCID 0000-0003-2619-1063 (M. Aleksander); 0000-0002-8981-5649 (Y. Kulakov); 0000-0003-2342-8475 (A. Deveciogullari); 0000-0002-2804-5556 (O. Zhurakovska); 0000-0003-0413-6274 (O. Havrylenko); 0009-0008-6811-1790 (D. Sytnyk)



© 2026 Copyright for this paper by its authors. Use permitted under Creative Commons License Attribution 4.0 International (CC BY 4.0).

In conventional networks, SDN provides a separation between the control plane and the data plane, simplifying centralized management of routing, load balancing, and quality-of-service policies. For classical communication channels, key performance indicators include bandwidth, packet transmission delay, jitter, packet loss rate, channel utilization, and network equipment power consumption. The centralized SDN controller enables real-time analysis of these metrics and supports decision-making regarding traffic rerouting, path reconfiguration, or traffic prioritization based on the current network state [1, 2].

In quantum networks, the role of SDN is even more significant due to the complexity of managing distributed quantum resources. Unlike classical networks, the performance of quantum channels is determined by such parameters as Quantum Bit Error Rate (QBER), secret key generation rate, probability of successful entanglement distribution, quantum state coherence time, decoherence level, photon losses, and the fidelity of quantum information transmission. The use of an SDN controller enables centralized monitoring of quantum resources, coordination of quantum repeater operations, dynamic selection of entanglement distribution routes, and integration of classical and quantum network segments into a unified management framework.

One of the distinctive features of software-defined quantum networks is their ability to support heterogeneous traffic types with different requirements for communication channel characteristics. Conventional traffic, including web requests, video streaming, multimedia services, cloud computing, and large-scale data transfer, primarily requires high bandwidth, low latency, and network scalability. These requirements are effectively satisfied by classical communication channels, which provide high transmission rates and efficient utilization of network resources. At the same time, certain categories of traffic require enhanced information security. These include cryptographic key distribution processes, secure inter-datacenter communications, data exchange within critical infrastructure systems, financial institutions, governmental information systems, and military networks. For such applications, quantum communication channels are particularly promising [3]. Despite their limited bandwidth and implementation complexity, they provide the ability to detect unauthorized interception attempts during information transmission due to the fundamental principles of quantum mechanics.

Therefore, modern network architectures can employ both classical and quantum communication channels simultaneously, enabling the support of different traffic types according to their specific requirements in terms of performance, reliability, and security. The efficient operation of such networks requires continuous monitoring and assessment of their condition. In classical networks, the network state is typically described by a set of parameters characterizing network topology, resource utilization, communication channel performance, and quality of service.

Formally, the state of a classical network can be defined as a vector of the most important metrics:

$$S_C(t) = \{BW, D, J, PLR, LU\}, \quad (1)$$

where:

$BW$  (bandwidth) — denotes the channel bandwidth;

$D$  (delay) — represents packet transmission delay;

$J$  (jitter) — denotes delay variation (jitter);

$PLR$  (packet loss ratio) — is the packet loss ratio;

$LU$  (link utilization) — represents the channel utilization level.

In classical networks, channel degradation is typically manifested through increased delay, packet losses, and network congestion.

In quantum networks, the concept of network state additionally encompasses quantum channel characteristics, entanglement-related parameters, decoherence indicators, QBER, the availability of quantum repeaters, and the utilization level of quantum resources:

$$S_Q(t) = \{QBER, SKR, F, PLR, A, T, ER, T_C, P_e\}, \quad (2)$$

where:

$QBER$  (quantum bit error rate) — denotes the quantum bit error rate;

$SKR$  (secret key rate) — represents the secret key generation rate;

$F$  (entanglement fidelity) — is the fidelity of the entangled state;

$PLR$  (photon loss rate) — denotes the photon loss rate;

$A$  (availability) — represents the channel availability coefficient;

$T$  (latency) — is the data transmission delay between network nodes;

$ER$  (entanglement Rate) — denotes the rate of generation or delivery of entangled pairs between network nodes (pairs/s);

$T_C$  (coherence time) — represents the coherence time;

$P_e$  (entanglement distribution success probability) — is the probability of successful entanglement distribution.

In quantum networks, similar indicators of channel degradation include an increase in  $QBER$ ; a decrease in  $SKR$ ; a reduction in entanglement fidelity ( $F$ ); an increase in  $PLR$ ; a decrease in  $A$ ; an increase in  $T$ ; a reduction in  $ER$ ; a decrease in  $T_C$ .

The development of a comprehensive (hybrid) network state model provides a holistic representation of the operational conditions of both the classical and quantum segments of the network infrastructure:

$$S_H(t) = S_C(t) \cup S_Q(t). \quad (3)$$

Network state analysis is a prerequisite for the timely detection of anomalies that may result from channel congestion, equipment failures, routing errors, cyberattacks, or degradation of quantum communication channels. In quantum networks, additional sources of anomalies include an increase in the quantum bit error rate, a reduction in the level of entanglement, decoherence of quantum states, and attempts at unauthorized interception of transmitted information. Therefore, the development of methods for assessing the state of hybrid SD-controlled networks represents an important scientific challenge aimed at enhancing the reliability, security, and operational efficiency of future quantum-classical networking infrastructures.

## 2. The Problem and the formulation of the task

The advancement of quantum communication technologies is driving the emergence of hybrid networks in which classical and quantum communication channels coexist and operate in an integrated manner. Classical networks are responsible for the transmission of control information and user traffic, whereas quantum channels are employed for secret key distribution and the provision of secure communication services. Such integration enables the combination of the high throughput and scalability of classical networks with the fundamentally new security mechanisms offered by quantum technologies.

The presence of large volumes of heterogeneous traffic, together with the simultaneous utilization of classical and quantum communication channels, considerably complicates network monitoring and operational state assessment. Under these conditions, the application of Software-Defined Networking (SDN) is particularly advantageous, as it provides centralized control of network resources, continuous collection of network-state information, and decision-support capabilities for routing, load balancing, and anomaly detection.

The scientific problem addressed in this study is the development of a method for assessing the state of a software-defined quantum network (SDQN) based on information describing the condition of its constituent quantum channels, as well as the identification of anomalous or degraded channels on the basis of the obtained assessment results.

### 3. Literature review

The current evolution of computer networks, data transmission technologies, and information security systems, particularly in the context of quantum communication deployment, is primarily focused on three interrelated directions: the development of a multilayer quantum Internet architecture, the integration of Quantum Key Distribution (QKD) services into conventional networking infrastructures, and the implementation of centralized control mechanisms based on Software-Defined Networking (SDN). In studies [4, 5, 6], quantum networks are considered not as isolated infrastructures but as integral components of future hybrid telecommunication systems, where classical channels are responsible for the transmission of control, multimedia, and bulk traffic, while quantum channels are employed for secret key distribution, entanglement distribution, and highly secure communication services.

A promising direction in the evolution of telecommunication systems is the development of software-defined quantum networks, which combine the capabilities of quantum information transmission with centralized network control mechanisms. Studies [7, 8, 9] demonstrate that an SDN controller can perform centralized orchestration of both quantum and classical resources, manage optical switches, QKD transceivers, key management systems, and security policies, while providing resource savings of 10–40%. This capability is particularly important in hybrid networks, where it is necessary to dynamically determine the most appropriate channel type for a given traffic category. Despite its advantages, the centralized SDN architecture introduces critical security vulnerabilities, particularly with respect to cyber threats such as Denial-of-Service (DoS) attacks, which may result in network degradation or even loss of network controllability. Consequently, there is a growing need for the development and deployment of additional protection mechanisms capable of ensuring the confidentiality, integrity, and availability of network management processes. In this context, methods for network state monitoring, real-time anomaly detection, and protection of the SDN controller against both external and internal threats become increasingly important. In [10], it was demonstrated that the QBER and SKR metrics can be utilized as time-series indicators for diagnosing the state of QKD channels and detecting channel degradation caused by photon losses and the influence of coexisting classical signals. These findings confirm the feasibility of representing the state of the quantum network segment by means of a vector of quantitative metrics  $S_Q(t) = \{QBER, SKR, F, PLR, T_C, P_e\}$ .

The increasing complexity of modern network infrastructures, the emergence of Software-Defined Networking (SDN), Internet of Things (IoT) technologies, and quantum communications have created the need for the development of novel approaches to network state monitoring and anomaly detection. Contemporary research has devoted significant attention to the application of machine learning and deep learning techniques for network traffic analysis, intrusion detection, and network service security enhancement. Studies [11, 12, 13] have demonstrated the effectiveness of deep learning approaches for attack and anomaly detection in SDN environments, making them suitable for deployment within the classical segment of hybrid network architectures. These studies also show that the centralized SDN architecture enables efficient collection of network data required for training anomaly detection models, while identifying the main vulnerabilities of SDN-based infrastructures, including distributed denial-of-service (DDoS) attacks against the controller, compromise of open interfaces, and attacks targeting the control plane.

An intrusion detection system for SDN environments based on machine learning techniques and specialized dataset balancing mechanisms was proposed in [14], demonstrating improved classification accuracy for network attacks. Furthermore, study [15] emphasized the potential of time-series analysis of network parameters for the detection of hidden anomalies. An important aspect of anomaly detection system design is the selection of representative datasets. In [16], a comprehensive analysis of modern datasets for SDN environments was conducted, highlighting the InSDN datasets, which are specifically designed to model realistic network operation scenarios and various attack types. In addition, study [17] investigated the integration of deep neural networks with blockchain technology for anomaly detection and prevention in Internet of Things environments, demonstrating the potential of combining intelligent network state analysis mechanisms with advanced cybersecurity technologies.

Unlike classical networks, anomalies in quantum communication systems may arise not only as a

consequence of network attacks or channel congestion but also due to physical processes associated with quantum information transmission. Such processes include quantum state decoherence, photon losses, entanglement degradation, and an increase in the quantum bit error rate. In [18], advances in anomaly detection for quantum networks were presented, where one-class anomaly detection techniques were proposed for identifying active attacks on the receiver side of quantum key distribution systems. The reported results demonstrated the high effectiveness of machine learning models in identifying previously unseen attack types in the absence of complete information regarding their characteristics. In [19], hybrid quantum-classical machine learning models were proposed for detecting photon-number-splitting and Trojan-horse attacks, further confirming the potential of artificial intelligence techniques for monitoring and securing quantum network infrastructures.

The analysis of contemporary research indicates that most existing approaches are focused on monitoring individual quantum channel parameters, such as QBER, SKR, photon loss rate, or entanglement fidelity. However, a unified model for representing the state of a quantum network, integrating quantum channel performance indicators, quantum resource conditions, and network traffic characteristics, is currently lacking. Furthermore, the problems of comprehensive anomaly detection and dynamic prioritization of virtual quantum channels based on the current network state remain insufficiently investigated. This limitation reduces both the efficiency of quantum resource utilization and the adaptability of quantum network infrastructures.

## 4. Problem statement

Since the quality of a SDQN must be determined based on information describing the state of all quantum channels comprising the network, we consider a cluster consisting of a set of quantum nodes, a set of quantum channels, and an SDN controller that serves as the central network management entity. The controller periodically collects information regarding the operational state of quantum nodes and communication channels. Therefore, within the scope of the considered problem, the network topology is not explicitly taken into account, and the cluster can be represented as a set of quantum channels forming the network infrastructure.

**Given:**

- $A = \{A_k \mid k = 1, \dots, n\}$  – is the set of quantum channels;
- $C = \{C_j \mid j = 1, \dots, m\}$  – is the set of criteria used to evaluate the channel characteristics that are important for both channel quality and the overall quality of the quantum network;
- $X = \{X_{kj} \mid k = 1, \dots, n; j = 1, \dots, m\}$  – is the set of evaluation values describing the quality (state) of the channels with respect to the criteria from the set  $C$ , where  $X_{kj}$  is the channel rating of  $A_k$  according to criterion  $C_j$ ;
- $W = \{W_j \mid j = 1, \dots, m\}$  – is the set of weighting coefficients associated with the criteria from the set  $C$ .

**Objective:** assess the overall state of the quantum network and identify anomalous and degraded quantum channels.

## 5. Justification of the proposed method

Since the state of quantum communication channels is characterized by a set of parameters whose values can be considered as evaluations with respect to predefined criteria, such as:

- photon loss probability;
- Quantum Bit Error Rate (QBER);
- secret key generation rate;
- entanglement fidelity;
- transmission latency;

- channel reliability;
- availability of quantum repeaters, etc.,

to assess the state of the network it is therefore necessary to solve a multi-criteria decision-making (MCDM) problem. The solution of this problem enables the ranking of quantum channels according to their operational condition, which subsequently allows the identification of anomalous or degraded channels and the determination of the overall state of the quantum network.

Several multi-criteria decision-making methods can be employed for channel ranking, including: SAW, TOPSIS, AHP, ELECTRE, VIKOR.

The SAW (Simple Additive Weighting) method [20, 21], also known as the weighted linear combination approach, is not well suited for ranking quantum communication channels because it assumes complete compensability among criteria. Consequently, poor performance with respect to one criterion can be compensated by exceptionally good performance in others. Such an assumption is often inappropriate for quantum channels, where certain characteristics, such as entanglement fidelity or photon loss probability, are critical and cannot be compensated by improvements in other parameters. Furthermore, the method is highly sensitive to normalization and scaling procedures and does not explicitly account for bottleneck criteria. In quantum communications, a single weak parameter, such as excessive decoherence, may render a channel practically unusable even when all other indicators remain satisfactory. The SAW method fails to capture such bottlenecks because the final evaluation is obtained through additive aggregation.

The TOPSIS method [20, 21, 22] is less dependent on simple linear compensation than SAW; however, it is based on Euclidean distance calculations, implicitly assuming comparable scaling and independence of criteria. This assumption is often violated in quantum communication systems, where parameters such as fidelity, entropy, photon losses, and decoherence are physically interrelated. In addition, TOPSIS is highly sensitive to the normalization procedure, and different normalization techniques may lead to substantially different ranking results, which is particularly problematic for quantum systems characterized by heterogeneous parameter scales. Similar to SAW, the TOPSIS method does not explicitly consider hard constraints, which represents a significant limitation in the assessment of quantum communication channels.

The AHP (Analytic Hierarchy Process) method [23] is widely used for determining criterion weights; however, it is not suitable for ranking a large number of quantum channels. The method is inherently subjective, as its results strongly depend on expert judgments, whereas the parameters considered in this study, such as fidelity, noise level, and entropy, are objective measurements that do not require expert evaluation. Furthermore, the dimensionality of pairwise comparison matrices increases significantly with the number of channels, resulting in substantial computational complexity.

The ELECTRE method [21, 24] is based on the construction of outranking relations that can be used to identify preferable alternatives. However, it does not always provide a complete ranking, as some alternatives may remain incomparable. Moreover, the method does not support the assessment of channel states through a unified ranking score. Another limitation is the complexity associated with defining and tuning the threshold values used in the construction of the outranking relations.

In contrast to the aforementioned approaches, the VIKOR method [21, 25, 26, 27] enables the consideration of physical characteristics that are particularly important for quantum communication channels. Specifically, even if a channel exhibits favorable average performance, an unacceptable value of a single critical parameter may render the channel unsuitable for operation. Within the VIKOR framework, such situations can be captured through a measure that reflects the maximum deviation from the ideal solution with respect to critical criteria. Since quantum channels are characterized by temporal variability, noise, decoherence, and stochastic photon losses, a channel that simultaneously achieves optimal values for all criteria is unlikely to exist. The VIKOR method is specifically designed to identify a compromise solution that is closest to the Pareto-optimal alternative, making it particularly suitable for dynamic networking environments. Unlike conventional criterion aggregation methods, VIKOR determines a compromise solution by simultaneously considering the overall utility of an alternative and its maximum individual regret relative to the ideal solution. This property prevents the selection

of channels with critically poor values of individual parameters and provides a more reliable ranking mechanism under the uncertainty and dynamic conditions inherent to quantum communication networks.

Therefore, the VIKOR method is considered an appropriate approach for assessing the state of quantum communication channels. However, the application of VIKOR produces only a ranking of channels, which alone is insufficient for determining the overall quality of the quantum network. To address this limitation, it is necessary to evaluate how the set of ranked channels relates to both an ideal positive channel and an ideal negative channel. An ideal positive channel is defined as a channel for which all parameter values attain their best possible values. Conversely, an ideal negative channel is defined as a channel whose parameter values are equal to the threshold values beyond which the corresponding criteria indicate a transition to a non-operational state. If the network analysis reveals channels for which at least one criterion violates its operational threshold, such channels are classified as non-operational. Subsequently, the problem is reduced to the classification of the operational states of the remaining channels within the quantum network.

To address this problem, the following method is proposed. Assume that the application of the multi-criteria decision-making procedure yields the following ranking of quantum channels:

$$A_{[1]} \succ A_{[2]} \succ \dots \succ A_{[n-1]} \succ A_{[n]}, \quad (4)$$

where  $A_{[i]}$  denotes the channel occupying the  $i$ -th position in the ranking.

Since the VIKOR method has been selected for ranking the channels, each channel  $A_{[i]}$  in ranking (4) is associated with a corresponding value  $Q(A_{[i]})$  representing the compromise index of the channel, which determines its position in the ranking.

It is evident that the following condition holds:

$$A^+ \succ A_{[1]} \succ A_{[2]} \succ \dots \succ A_{[n-1]} \succ A_{[n]} \succ A^-, \quad (5)$$

where  $A^+$ ,  $A^-$  are the “ideal” channels characterized by the best and the worst (threshold) values of all criteria, respectively.

Let us introduce the following measures:

$d_{[i]}^+$  – the Euclidean distance between channel  $A_{[i]}$  and the “ideal” positive channel  $A^+$  in the  $m$ -dimensional criterion space;

$d_{[i]}^-$  – the Euclidean distance between channel  $A_{[i]}$  and the “ideal” negative channel  $A^-$  in the  $m$ -dimensional criterion space;

$$P_{[i]} = \frac{d_{[i]}^-}{d_{[i]}^- + d_{[i]}^+} - \text{channel rating } A_{[i]}, \quad P_{[i]} \in [0, 1]. \quad (6)$$

Then the following condition holds:

$$\begin{aligned} P_{[i]} &= 0, & \text{if } A_{[i]} &= A^- \\ P_{[i]} &= 1, & \text{if } A_{[i]} &= A^+ \end{aligned}$$

Therefore, it is evident that the following condition holds for ranking (5):

$$0 < P_{[n]} < P_{[1]} < 1. \quad (7)$$

Any channel operating in a functional state can be represented as a point within the interval  $[0, 1]$ . Partitioning the interval  $[0, 1]$  into subintervals corresponding to different quantum channel states enables the determination of the channel condition. The interval boundaries and the corresponding channel states are presented in Table 1.

The division into three classes – marginal, degraded, high-quality – is based on the inherent property of quantum communication channels, namely their nonlinear performance degradation. In quantum

**Table 1**  
Quantum Channel States

| State Name          | Designation | Interval     |
|---------------------|-------------|--------------|
| Non-operational     | $S_5$       | —            |
| Marginal            | $S_4$       | $< 0.3$      |
| Moderate degraded   | $S_3$       | $[0.3, 0.5)$ |
| Noticeable degraded | $S_2$       | $[0.5, 0.7)$ |
| High-quality        | $S_1$       | $[0.7, 1]$   |

communication systems, a reduction in channel quality does not result in a proportional decrease in effective throughput. Instead, an extended transition region emerges in which the channel remains operational but requires significant resources for error correction, entanglement purification, and retransmission procedures. The threshold values of 0.3 and 0.7 were selected as heuristic boundaries separating different operational regimes and serve as decision boundaries in the channel-state classification problem. The interval  $[0.7, 1]$  corresponds to a stable operating regime characterized by a low noise level and the absence of substantial compensation requirements. The interval  $[0.3, 0.7)$  represents an operational but degraded regime, in which the channel remains functional; however, the efficiency of quantum communication protocols is significantly reduced due to the need for error correction and entanglement purification mechanisms. The additional subdivision of the degraded region into moderate and significant degradation using a threshold value of 0.5 reflects the nonlinear nature of quantum channel performance deterioration. In particular, the cost of error correction and entanglement purification increases nonlinearly, resulting in two distinct operational regimes within the degraded state. Values below 0.3 correspond to a near-failure regime, in which the amount of useful information becomes comparable to the noise level. It should be noted that these threshold values are configurable and may be adjusted depending on the quantum communication protocol and the constraints of a particular implementation.

Linear scaling of all points  $Q(A_{[i]})$  from the interval defined by the endpoints  $Q(A_{[n]})$  and  $Q(A_{[1]})$ , onto the interval  $[P_{[n]}, P_{[1]}]$  makes it possible to determine the state of each channel according to the membership of the corresponding point  $Q(A_{[1]})$  in the interval associated with a particular channel-state class.

Based on the identified states of individual channels, conclusions can be drawn regarding the overall condition and quality of the quantum network as a whole. The thresholds for network state classification are defined using an expert-driven partitioning of the normalized network performance index  $N \in [0, 1]$ :

$$N = \sum_{i=1}^4 v_i r_i, \quad (8)$$

where  $v_1 = 1, v_2 = 0.7, v_3 = 0.5, v_4 = 0.3$ ;

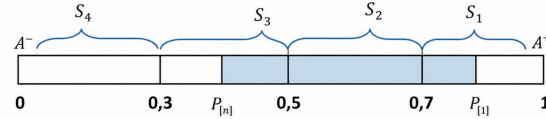
$r_i$  denotes the proportion of channels belonging to state  $S_i$ , relative to the total number of channels in the network.

The network states and the corresponding intervals associated with the network performance index  $N$  are presented in Table 2.

**Table 2**  
Network States

| Network State | Interval ( $N$ ) |
|---------------|------------------|
| Critical      | $\leq 0.3$       |
| Degraded      | $(0.3, 0.5]$     |
| Operational   | $(0.5, 0.7]$     |
| High-quality  | $(0.7, 1]$       |

The interval boundaries (Fig. 1) are selected to reflect the nonlinear degradation behavior of quantum communication channels, where performance does not decrease linearly with noise and loss. In particular, the range  $[0.7, 1]$  corresponds to stable operation with negligible error-correction overhead, while  $[0.5, 0.7)$  represents an operational regime with moderate compensation requirements. The interval  $[0.3, 0.5)$  denotes degraded performance, where quantum error correction and entanglement purification significantly affect system efficiency. Values less than or equal to 0.3 indicate a critical regime approaching communication failure, consistent with the rapid deterioration of quantum key generation rates under high noise conditions.

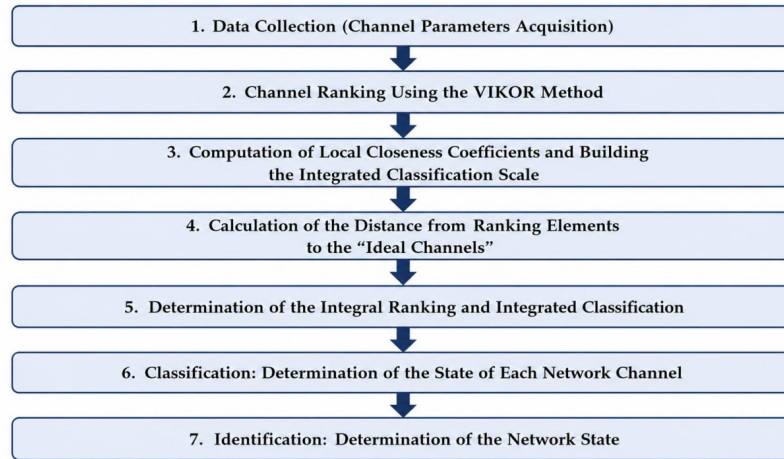


**Figure 1:** The interval boundaries.

The threshold values used for the aggregated classification are defined heuristically and may be adjusted depending on the network scale, the type of quantum communication protocol, and the required level of transmission reliability.

## 6. Method for quantum network state assessment

The stages of the proposed method for assessing the state of a SDQN based on channel-state evaluation are presented in Fig. 2.



**Figure 2:** Proposed method workflow.

**Step 1.** At this stage, the SDQN controller periodically polls the network channels and collects channel-state information in the form of criterion evaluation vectors:

$$C = \{QBER, Fidelity, Loss, Availability, Latency, EntanglementRate\}.$$

**Step 2.** Generate a ranking of the channels from the set  $A$  using the VIKOR multi-criteria decision-making method.

**2.1.** Construct the input data matrix based on the collected channel parameters (Table 3).

The criterion weights are determined either by expert assessment or experimentally using statistical methods.

**Table 3**  
Input Data Matrix

| Channels | Criteria     |                  |              |                |                 |                      |
|----------|--------------|------------------|--------------|----------------|-----------------|----------------------|
|          | $C_1$ (QBER) | $C_2$ (Fidelity) | $C_3$ (Loss) | $C_4$ (Avail.) | $C_5$ (Latency) | $C_6$ (Entang. Rate) |
| $A_1$    | $x_{11}$     | $x_{12}$         | $x_{13}$     | $x_{14}$       | $x_{15}$        | $x_{16}$             |
| $A_2$    | $x_{21}$     | $x_{22}$         | $x_{23}$     | $x_{24}$       | $x_{25}$        | $x_{26}$             |
| $\dots$  | $\dots$      | $\dots$          | $\dots$      | $\dots$        | $\dots$         | $\dots$              |
| $A_n$    | $x_{n1}$     | $x_{n2}$         | $x_{n3}$     | $x_{n4}$       | $x_{n5}$        | $x_{n6}$             |
| Weight   | $w_1$        | $w_2$            | $w_3$        | $w_4$          | $w_5$           | $w_6$                |

**2.2.** For each criterion  $C_j$  determine the range of evaluation values (the best and the worst values):

$$x_j^* = \max_k f_{kj}, \quad x_j^- = \min_k f_{kj} \quad (\text{if higher values are preferable for the criterion}),$$

$$x_j^- = \max_k f_{kj}, \quad x_j^* = \min_k f_{kj} \quad (\text{if lower values are preferable for the criterion}).$$

**2.3.** Compute the VIKOR functions for each channel (Table 4):

**Table 4**  
Method Functions Calculated for Each Channel

| Symbol | Name                      | Interpretation for a Quantum Channel                                             |
|--------|---------------------------|----------------------------------------------------------------------------------|
| $S_j$  | Group Utility Measure     | Aggregate channel quality assessment considering all evaluation criteria         |
| $R_j$  | Individual Regret Measure | Assessment of the worst-performing channel characteristic (bottleneck criterion) |
| $Q_j$  | Compromise Index          | Overall channel state index / Quantum Channel State Index                        |

$$S_k = \sum_{j=1}^m w_j \frac{|x_j^* - x_{kj}|}{|x_j^* - x_j^-|}, \quad (9)$$

$$R_k = \max_j \left\{ w_j \frac{|x_j^* - x_{kj}|}{|x_j^* - x_j^-|} \right\}, \quad j = 1, \dots, m, \quad (10)$$

$$Q_k = v \frac{S_k - S^*}{S^- - S^*} + (1 - v) \frac{R_k - R^*}{R^- - R^*}, \quad (11)$$

where:

$$S^* = \min_k S_k,$$

$$S^- = \max_k S_k,$$

$$R^* = \min_k R_k,$$

$$R^- = \max_k R_k,$$

$v \in [0, 1]$  is the compromise index.

**2.4.** Rank the quantum channels in ascending order of the compromise index (lower values of  $Q_j$  correspond to channels with better overall performance and quality characteristics). As a result of Step 2, the channel ranking defined by expression (4) is obtained.

**Step 3.** Determination of network channel states.

3.1. Construct  $A^+$ ,  $A^-$  – the “ideal” channels representing the ideal positive and ideal negative channels, respectively.

3.2. Calculate the Euclidean distances between  $A^+$  and  $A_{[1]}$ , and also between  $A_{[n]}$  and  $A^-$ .

3.3. Calculate the coordinates of the boundary points  $A_{[1]}$ ,  $A_{[n]}$  of the ranking interval using expression (6), and map these points onto the interval  $[0, 1]$ .

3.4. Using linear scaling, project all points of the ranking interval onto  $[0, 1]$ , while preserving the relative distances between them according to the values of the  $Q$  function obtained in Step 2.

3.5. Determine the state of each channel according to its position within  $[0, 1]$ , using the classification scale presented in Table 1. Calculate the number of channels belonging to each state category.

3.6. Based on the results obtained in Step 3.5, calculate the Network Performance Index according to expression (8) and classify the overall network state using the intervals defined in Table 2.

3.7. To enable a more comprehensive analysis of the network condition and support decision-making, form a set of channels classified as non-operational and a set of channels classified as marginal.

## 7. Experimental evaluation

The experimental evaluation was conducted on synthetically generated clusters of software-defined quantum networks comprising from 20 to 50 quantum nodes. This range of network sizes was selected to assess the effectiveness and scalability of the proposed method under different levels of network complexity.

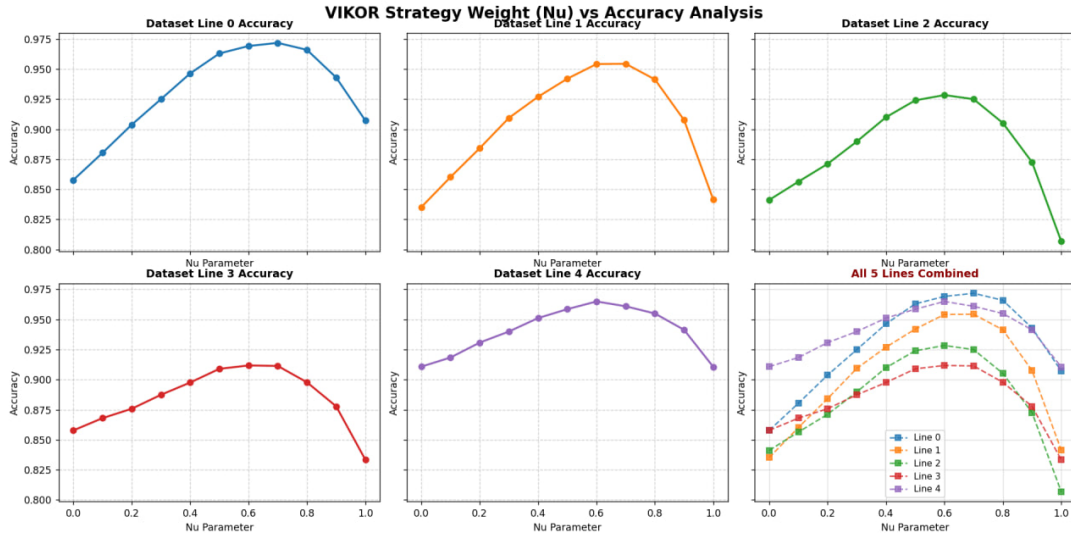
The relative importance of the evaluation criteria is taken into account through a vector of weighting coefficients:

$$W = \{w_1, w_2, \dots, w_6\}, \quad \text{where } \sum_{j=1}^6 w_j = 1. \quad (12)$$

During the experimental evaluation, the criterion weights are systematically varied according to predefined weighting strategies (Fig. 3), while all other decision-making parameters remain unchanged. In particular, the baseline scenario  $W_1$  assumes equal importance of all criteria. Such an experimental design enables a sensitivity analysis of the proposed method with respect to changes in criterion priorities and allows the assessment of their impact on the accuracy of anomalous channel detection and on the reliability of the overall quantum network state assessment.

| ID | QBER   | Fidelity | Loss   | Availability | Latency | Entanglement Rate |
|----|--------|----------|--------|--------------|---------|-------------------|
| W1 | 0.1667 | 0.1667   | 0.1667 | 0.1667       | 0.1667  | 0.1667            |
| W2 | 0.2500 | 0.2000   | 0.1500 | 0.1000       | 0.1000  | 0.2000            |
| W3 | 0.3500 | 0.2500   | 0.1500 | 0.1000       | 0.0500  | 0.1000            |
| W4 | 0.1500 | 0.2000   | 0.1500 | 0.1000       | 0.1000  | 0.3000            |
| W5 | 0.2353 | 0.2353   | 0.2353 | 0.0588       | 0.0588  | 0.1765            |
| W6 | 0.0667 | 0.0667   | 0.0667 | 0.3333       | 0.3333  | 0.1333            |
| W7 | 0.4211 | 0.3158   | 0.1053 | 0.0526       | 0.0526  | 0.0526            |
| W8 | 0.1579 | 0.2632   | 0.3158 | 0.0526       | 0.0526  | 0.1579            |
| W9 | 0.1053 | 0.1053   | 0.0526 | 0.3158       | 0.2105  | 0.2105            |

**Figure 3:** Weighting coefficient distribution scenarios used for sensitivity analysis of the proposed quantum network state assessment method.



**Figure 4:** Effect of the VIKOR parameter  $\nu$  on classification accuracy.

Figure 4 presents the results of the analysis of the influence of the VIKOR parameter  $\nu$  on the classification accuracy for five channel-state datasets (Dataset Line 0–4).

**General trend.** A similar pattern can be observed across all datasets:

- The classification accuracy gradually increases as the parameter  $\nu$  grows from 0 to approximately 0.6–0.7;
- The highest accuracy values are achieved within the interval  $\nu = 0.6 - 0.7$ ;
- Further increases in  $\nu$  result in a decrease in classification accuracy;
- The largest performance degradation is observed at  $\nu = 1$ .

These results indicate that excessive bias of the VIKOR method toward individual alternative preference deteriorates the quality of decision-making, whereas balanced values of  $\nu$  provide the most accurate results.

#### Dataset Line 0:

- Initial accuracy is approximately 0.86;
- Accuracy gradually increases and reaches a maximum of 0.97 at  $\nu \approx 0.7$ ;
- After  $\nu = 0.8$  the accuracy decreases to approximately 0.91 at  $\nu = 1$ .

#### Dataset Line 1:

- Accuracy increases from approximately 0.84 to 0.95;
- The maximum value is achieved within the interval  $\nu = 0.6 - 0.7$ ;
- At  $\nu = 1$  the accuracy drops sharply to approximately 0.84.

#### Dataset Line 2:

- This dataset exhibits the lowest accuracy among all datasets;
- The maximum accuracy reaches approximately 0.93 at  $\nu = 0.6 - 0.7$ ;
- The largest decline is observed at  $\nu = 1$  where the accuracy decreases to approximately 0.81.

### Dataset Line 3:

- Accuracy increases from approximately 0.86 to 0.91;
- The optimal region corresponds to  $\nu = 0.6 - 0.7$ ;
- After  $\nu = 0.8$  the accuracy rapidly decreases to approximately 0.83.

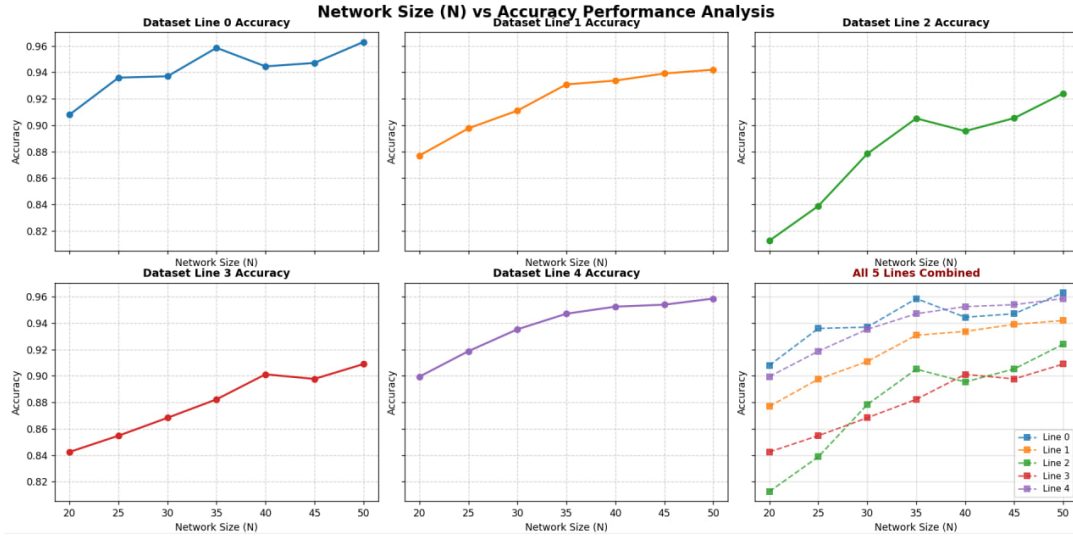
### Dataset Line 4:

- This dataset demonstrates the highest overall classification accuracy;
- Accuracy increases from approximately 0.91 to a maximum value of about 0.97;
- Even after the decrease observed at  $\nu = 1$  the accuracy remains relatively high ( $\approx 0.91$ ).

**Combined (All 5 Lines Combined):** The aggregated graph confirms a consistent behaviour across all five datasets:

- The interval  $\nu = 0.6 - 0.7$  represents a common region of maximum classification accuracy;
- For small values of  $\nu < 0.2$  the accuracy is noticeably lower;
- When  $\nu > 0.8$  a gradual degradation of performance is observed;
- The value  $\nu = 1$  is the least effective setting for almost all datasets.

The obtained results demonstrate that the parameter  $\nu$  has a significant impact on the performance of the VIKOR method. For all considered datasets, the highest classification accuracy is achieved at  $\nu \approx 0.6 - 0.7$ , where an optimal balance between group utility and individual regret is maintained.



**Figure 5:** The effect of network size on classification accuracy.

Figure 5 presents the results of the analysis of the impact of network size (*NetworkSize*,  $N$ ) on the classification accuracy for five channel-state datasets (Dataset Line 0–4).

**General characteristics.** A positive relationship between network size and classification accuracy can be observed across all datasets. As the number of network nodes increases from  $N = 20$  to  $N = 50$ , the classification accuracy generally improves, although minor local fluctuations are observed for some datasets.

**Dataset Line 0.** For the first dataset, the classification accuracy increases from approximately 0.91 at  $N = 20$  to 0.96 at  $N = 50$ . The most significant improvement is observed during the initial phase of network expansion. After  $N = 35$ , minor fluctuations occur; however, the overall trend remains positive.

**Dataset Line 1.** The second dataset demonstrates a steady increase in accuracy from approximately 0.88 to 0.94. The corresponding curve exhibits an almost linear behavior, indicating a positive influence of increasing network size on model performance.

**Dataset Line 2.** The third dataset exhibits the largest improvement in classification accuracy among all considered datasets. The accuracy increases from approximately 0.81 at  $N = 20$  to 0.92 at  $N = 50$ . A slight decrease observed at  $N = 40$  does not affect the overall upward trend.

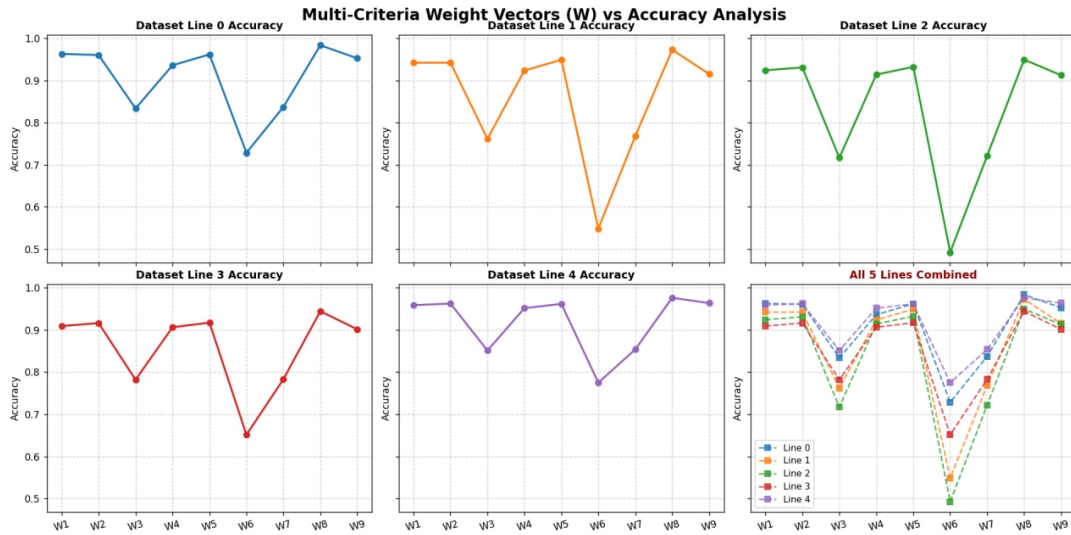
**Dataset Line 3.** For the fourth dataset, the classification accuracy increases from approximately 0.84 to 0.91. A temporary minor decrease is observed after  $N = 40$ . However, the accuracy rises again at  $N = 50$ .

**Dataset Line 4.** The fifth dataset is characterized by the highest accuracy values throughout the experiment. The accuracy increases from approximately 0.90 to 0.96, demonstrating smooth and stable growth as the network size increases.

**Combined.** The aggregated graph confirms a common trend across all five channel-state datasets:

- Increasing the network size leads to higher classification accuracy;
- The largest improvement is observed within the range  $N = 20 \dots 35$ ;
- Beyond  $N = 35 \dots 40$ , the rate of improvement gradually decreases;
- At  $N = 50$ , all curves achieve their maximum or near-maximum accuracy values.

The obtained results indicate that increasing the network size has a positive effect on the performance of the proposed model. The highest classification accuracy for all considered datasets is achieved at  $N = 50$ . However, beyond  $N = 35 \dots 40$ , the benefit of further network expansion becomes less pronounced, suggesting that the system approaches a saturation region in which additional network resources provide only marginal improvements in classification accuracy.



**Figure 6:** Influence of criterion weighting coefficients on classification accuracy.

Figure 6 presents the results of the analysis of the influence of criterion weighting coefficients on the classification accuracy for five channel-state datasets. The horizontal axis represents different weighting strategies for the criteria used in quantum network quality assessment (Figure 3).

**General characteristics.** The obtained results demonstrate that the selection of criterion weights has a significant impact on classification accuracy. For most datasets, the highest performance is achieved using weighting strategies  $W_8$ ,  $W_4$ ,  $W_1$ , and  $W_5$ , whereas the lowest accuracy is consistently observed for  $W_6$ .

**Dataset Line 0.** For the first dataset, the classification accuracy ranges from approximately 0.73 to 0.98. The highest accuracy is achieved using strategy  $W_8$ , while the lowest value is observed for  $W_6$ . Strategies  $W_1$ ,  $W_2$ , and  $W_5$  also provide high accuracy values exceeding 0.95.

**Dataset Line 1.** The second dataset demonstrates a similar trend. The maximum accuracy is approximately 0.97 for strategy  $W_8$ , whereas the minimum accuracy is approximately 0.55 for  $W_6$ . These results indicate that variations in criterion weights have a substantial impact on classification performance.

**Dataset Line 2.** For the third dataset, the best results are obtained using strategies  $W_8$ ,  $W_4$ , and  $W_5$ , yielding accuracy values in the range of approximately 0.93–0.95. The lowest accuracy is observed for  $W_6$ , reaching approximately 0.49, which represents the minimum value among all considered datasets.

**Dataset Line 3.** For the fourth dataset, the classification accuracy varies from approximately 0.65 to 0.94. The highest value is achieved with strategy  $W_8$ , whereas  $W_6$  again demonstrates the poorest performance.

**Dataset Line 4.** The fifth dataset exhibits the most stable results. The classification accuracy exceeds 0.85 for almost all weighting strategies, while the maximum value of approximately 0.98 is achieved using  $W_8$ . The lowest accuracy is observed for  $W_6$  (approximately 0.78).

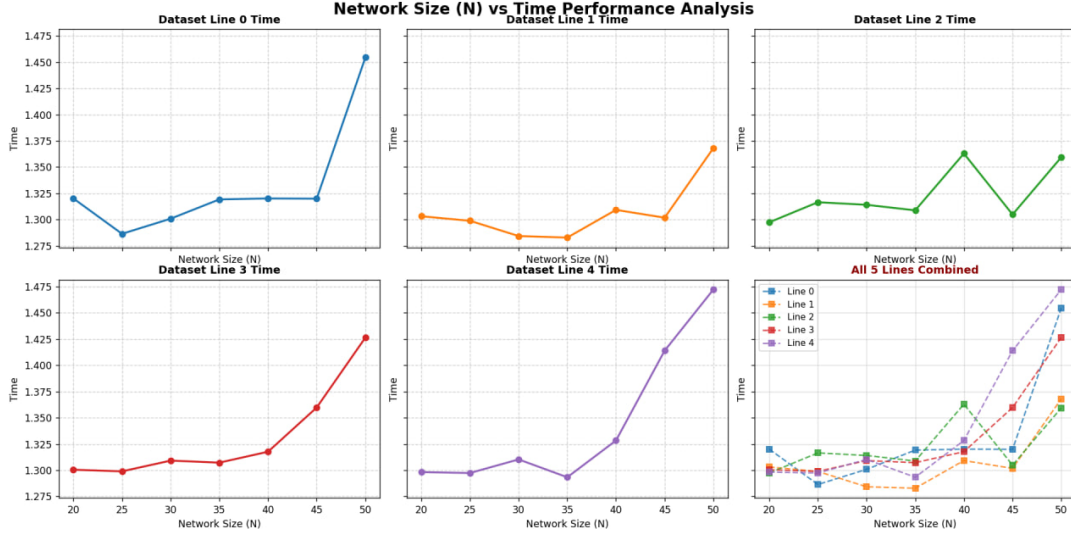
**Combined.** The aggregated results reveal several common patterns:

- Weighting strategies  $W_1$ ,  $W_4$ ,  $W_5$ , and  $W_8$  provide consistently high classification accuracy across all datasets;
- Strategy  $W_3$  demonstrates a moderate reduction in accuracy;
- Strategy  $W_7$  yields intermediate performance;
- Strategy  $W_6$  is the most problematic, exhibiting a substantial decrease in classification accuracy for all datasets;
- For strategies  $W_7$ ,  $W_8$ , and  $W_9$ , classification accuracy increases significantly.

The obtained results indicate that the selection of criterion weighting coefficients is one of the key factors affecting the effectiveness of multi-criteria decision-making in quantum network state assessment. The best performance is achieved by strategies  $W_8$ ,  $W_4$ ,  $W_1$ , and  $W_5$ , which demonstrate high and stable classification accuracy across all datasets. In contrast, strategy  $W_6$  substantially degrades classification performance, indicating excessive concentration of weights on individual criteria and a loss of balance among the considered network characteristics. These findings confirm the importance of balanced weighting schemes for the development of reliable quantum channel quality assessment models based on multi-criteria decision-making methods.

Figure 7 presents the results of the analysis of the impact of network size on the algorithm execution time for five datasets (Dataset Line 0-4).

**General characteristics.** The obtained results indicate that the algorithm execution time generally increases as the network size grows. For most datasets, relatively stable performance is observed for small and medium-sized networks within the range 20 . . . 40, whereas a more pronounced increase in execution time occurs when the number of nodes reaches 45 . . . 50. This behavior reflects the increase in computational complexity associated with network scaling.



**Figure 7:** Influence of network size on the algorithm execution time.

**Dataset Line 0.** For the first dataset, the execution time remains nearly constant within the range  $N = 20 \dots 45$ , varying between approximately 1.29 and 1.32 seconds. At  $N = 50$ , a significant increase to approximately 1.46 seconds is observed, representing the maximum value for this dataset.

**Dataset Line 1.** The second dataset exhibits the most stable behavior. Within the range  $N = 20 \dots 45$ , the execution time remains almost unchanged (approximately 1.28–1.31 seconds), increasing to approximately 1.37 seconds only at  $N = 50$ .

**Dataset Line 2.** For the third dataset, minor fluctuations in execution time are observed. The maximum value of approximately 1.36 seconds is reached at  $N = 40$ . Following a slight decrease at  $N = 45$ , the execution time increases again at  $N = 50$ .

**Dataset Line 3.** The fourth dataset demonstrates a gradual increase in execution time as the network size grows. The execution time rises from approximately 1.30 seconds at  $N = 20$  to 1.43 seconds at  $N = 50$ . The most noticeable increase occurs beyond  $N = 40$ .

**Dataset Line 4.** The fifth dataset exhibits the highest sensitivity to network scaling. Up to  $N = 35$ , the execution time remains nearly constant; however, after  $N = 40$ , a rapid increase is observed, from approximately 1.33 seconds to 1.47 seconds at  $N = 50$ , representing the highest execution time among all datasets.

**Combined.** The aggregated graph confirms a common trend across all five datasets:

- Increasing the network size leads to longer algorithm execution times;
- Within the range  $N = 20 \dots 40$ , execution times vary only slightly;
- Beyond  $N = 40$ , most datasets exhibit accelerated growth in execution time;
- The maximum execution times are observed at  $N = 50$ ;
- Dataset Line 4 demonstrates the highest computational cost, whereas Dataset Line 1 exhibits the greatest stability.

The obtained results indicate that the proposed approach demonstrates good scalability for small and medium-sized quantum networks. However, increasing the number of network nodes beyond 40 leads to a noticeable growth in computational overhead, which can be attributed to the increasing complexity

of information processing and the growing number of potential interactions among quantum network elements.

## 8. Conclusions

This paper addressed the problem of assessing the state of software-defined quantum networks and detecting anomalous or degraded communication channels. The conducted literature review demonstrated that existing approaches are primarily focused on monitoring individual quantum channel parameters and do not provide a comprehensive assessment of the overall network state.

To solve this problem, a method for software-defined quantum network state assessment based on a multi-criteria decision-making approach was proposed. The method employs such indicators as QBER, Fidelity, Loss, Availability, Latency, and Entanglement Rate to construct an integrated assessment of quantum channel conditions. The VIKOR method was applied to rank quantum channels, enabling the consideration of conflicting criterion effects and the identification of a compromise solution closest to the ideal channel state.

A channel classification approach based on the proximity of channels to positive and negative reference states was proposed, together with a method for aggregating channel-level assessments into an overall network state indicator. This approach makes it possible not only to identify non-operational, anomalous, and degraded channels but also to evaluate the operational quality of the quantum network as a whole.

The experimental evaluation confirmed the effectiveness of the proposed software-defined quantum network state assessment method. The results demonstrated that the classification accuracy depends on the VIKOR parameter  $\nu$ , the weighting coefficient distribution strategy, and the network size. The highest accuracy was achieved under balanced parameter settings and criterion weighting schemes. The obtained results indicate high accuracy, robustness, and scalability of the proposed method, confirming its suitability for overall network state assessment and anomaly detection in quantum communication networks.

The practical significance of the proposed approach lies in its applicability to SDQN monitoring and management systems for supporting decision-making related to routing, resource allocation, and timely response to quantum channel degradation. The obtained results provide a foundation for the development of intelligent quantum network management systems and may serve as a component of automated anomaly detection frameworks for next-generation communication networks.

Future research directions include the development of methods for automatic determination of criterion weights, the generation of realistic datasets for quantum networking environments, and the integration of the proposed approach with machine learning techniques for network state prediction and real-time anomaly detection.

## Declaration on Generative AI

The authors have not employed any Generative AI tools.

## References

- [1] A. Volokyta, A. Kogan, O. Cherevatenko, D. Korenko, D. Oboznyi, Y. Kulakov, Traffic engineering with specified quality of service parameters in software-defined networks, *International Journal of Computer Network and Information Security* (2024) 1–13. doi:10.5815/ijcnis.2024.05.01.
- [2] Y. Kulakov, D. Oboznyi, Method of dynamic reconfiguration of software-defined networks, *Information, Computing and Intelligent Systems* (2024) 25–36. doi:10.20535/2786-8729.4.2024.305095.
- [3] Z. Hu, S. Gnatyuk, O. Koval, V. Gnatyuk, S. Bondarovets, *International Journal of Computer Network and Information Security* (2017) 10–21.

- [4] Z. Zhang, C. Papagianni, F. Speelman, P. Grosso, Toward complete quantum network stacks, *IEEE Network* 38 (2024) 153–159. doi:10.1109/MNET.2024.3402951.
- [5] A. Meddeb, Quantum internet building blocks state of research and development, *Computer Networks* (2025). doi:10.1016/j.comnet.2025.111151.
- [6] J. Liu, T. Le, T. Ji, R. Yu, D. Farfurnik, G. Byrd, D. Stancil, The road to quantum internet: Progress in quantum network testbeds and major demonstrations, *Progress in Quantum Electronics* (2025). doi:10.1016/j.pquantelec.2024.100551.
- [7] J. C. Hernandez-Hernandez, D. Larrabeiti, M. Calderon, I. Soto, B. Cimoli, H. Liu, I. T. Monroy, Designing optimal quantum key distribution networks based on time-division multiplexing of qkd transceivers: qtdm-qkdn, *Future Generation Computer Systems* 164 (2025) 107557. doi:10.1016/j.future.2024.107557.
- [8] J. S. Buruaga, R. B. Mendez, J. P. Brito, V. Martin, Hybrid quantum-safe integration of tls in sdn networks, *Computer Network* (2025) 1–17.
- [9] P. James, S. Laschet, S. Ramacher, L. Torresetti, Key management systems for large-scale quantum key distribution networks, in: *Proceedings of ARES '23*, 2023. doi:10.1145/3600160.3605050.
- [10] G. Maragkopoulos, A. Mandilara, T. Nikas, D. Syvridis, Real-time diagnostics on a qkd link via qber time-series analysis, *Entropy* 26 (2024) 922. doi:10.3390/e26110922.
- [11] B. Shyryn, T. A. Ahanger, A. Zhumadillayeva, Enhancing software-defined network security with deep learning: a comprehensive review, *International Journal of Information Security* 25 (2026).
- [12] V. G. d. S. Ruffo, et al., Anomaly and intrusion detection using deep learning for software-defined networks, *Expert Systems with Applications* (2024). doi:10.1016/j.eswa.2024.124982.
- [13] A. H. Janabi, T. Kanakis, M. Johnson, Intrusion detection system in software-defined networking, *IEEE Access* 12 (2024) 164097–164120. doi:10.1109/ACCESS.2024.349338.
- [14] S. Chatzimiltis, S. R. Lucas, M. Shojafar, M. B. Mashhadi, R. Tafazolli, Intrusion detection in software defined networks with imbalanced attack classes, *ITU Journal on Future and Evolving Technologies* 5 (2024) 422–432.
- [15] F. M. Anis, M. Alabdullatif, S. Aljbli, M. Hammoudeh, A survey on the applications of deep learning in network intrusion detection systems to enhance network security, *IEEE Access* 13 (2025) 185357–185373. doi:10.1109/ACCESS.2025.3624952.
- [16] H. Y. I. Khalid, N. B. I. Aldabagh, A survey on the latest intrusion detection datasets for software defined networking environments, *Engineering, Technology & Applied Science Research* 14 (????) 13190–13200.
- [17] A. R. Sathyabama, J. Katiravan, Enhancing anomaly detection and prevention in internet of things (iot) using deep neural networks and blockchain based cyber security, *Scientific Reports* (2025). doi:10.1038/s41598-025-04164-4.
- [18] J. Liu, B. Huang, J. Su, Q. Peng, A. Huang, Deep anomaly detection for active attacks on the receiver in quantum key distribution, *Optics Express* 33 (2025) 47137–47150. doi:10.1364/OE.575434.
- [19] A. Al-Kuwari, N. Mohamed, S. Al-Kuwari, A. Farouk, B. K. Behera, Resisting quantum key distribution attacks using quantum machine learning, *IET Quantum Communication* (2026) 1–18. doi:10.1049/qtc2.70028.
- [20] F. Ciardiello, A. Genovese, A comparison between topsis and saw methods, *Annals of Operations Research* 325 (2023) 967–994. doi:10.1007/s10479-023-05339-w.
- [21] S. K. Effatpanah, et al., Comparative analysis of five widely-used multi-criteria decision-making methods to evaluate clean energy technologies: A case study, *Sustainability* 14 (2022) 1403. doi:10.3390/su14031403.
- [22] V. Pandey, Komal, H. Dincer, A review on topsis method and its extensions for different applications with recent development, *Soft Computing* 27 (2023) 18011–18039. doi:10.1007/s00500-023-09011-0.
- [23] M. Ashour, A. Mahdiyar, A comprehensive state-of-the-art survey on the recent modified and hybrid analytic hierarchy process approaches, *Applied Soft Computing* 150 (2024) 111014. doi:10.1016/j.asoc.2023.111014.
- [24] H. Taherdoost, M. Madanchian, A comprehensive overview of the electre method in multi-

- criteria decision-making, *Journal of Management Science & Engineering Research* 6 (2023) 5–16. doi:10.30564/jmser.v6i2.5637.
- [25] D. Yu, T. Ye, Uncovering the academic evolution of vikor method: a comprehensive main path analysis, *Journal of the Operational Research Society* 76 (2025) 393–409. doi:10.1080/01605682.2024.2359726.
- [26] J. Fan, D. Han, M. Wu, Picture fuzzy additive ratio assessment method (aras) and visekriterijumska optimizacija i kompromisno resenje (vikor) method for multiattribute decision problem and their application, *Complex & Intelligent Systems* 9 (2023) 5345–5357. doi:10.1007/s40747-023-01007-5.
- [27] E. J. Yazo-Cabuya, A. Ibeas, J. A. Herrera-Cuartas, Integration of sustainability in risk management and operational excellence through the vikor method considering comparisons between multicriteria decision-making methods, *Sustainability* 16 (2024) 4585. doi:10.3390/su16114585.