International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

# AI-Assisted Real-Time Satellite Quantum Key Distribution Simulator with Hybrid Noise Modeling and Finite-Size Security Analysis

V. Sharmila, P. Gnana Priya, V. Gnana Prasanna, K. Poongodi
Department of Artificial Intelligence and Data Science, Kingston Engineering College, Vellore,
Tamil Nadu, India

**Abstract - Satellite-based Quantum Key Distribution (QKD) has emerged as a promising solution for global secure communication beyond the limitations of terrestrial optical fiber networks. However, practical free-space optical (FSO) satellite channels are highly dynamic due to atmospheric turbulence, background radiation, weather variability, and finite transmission durations. Most existing models rely on static channel assumptions and asymptotic secret key rate (SKR) estimations, which do not accurately reflect real-time operational conditions. This paper proposes an AI-assisted real-time satellite Continuous Variable QKD (CV-QKD) simulator that integrates live weather data with machine learning- based hybrid noise prediction to model realistic channel behavior. The predicted noise parameters are incorporated into an adaptive QKD framework to dynamically compute both asymptotic and finite-size corrected SKR values. The system further performs day–night comparative analysis and 24-hour temporal simulation to study channel variations over time. All operational parameters, including predicted noise, adaptive SKR, and finite-size adjustments, are logged for reproducibility and performance evaluation. The proposed work implemented in the QKD simulator bridges the gap between theoretical QKD modeling and practical satellite deployment by introducing environmental awareness, AI-driven channel adaptation, and finite-size security considerations within an interactive visualization platform. This framework provides a scalable and realistic tool for analyzing next-generation satellite quantum communication systems.**

**Key Terms- Continuous Variable Quantum Key Distribution (CV-QKD), free-space optical (FSO), optical fiber networks, Asymptotic secret key rate (SKR), finite-size, 24-hour temporal simulation, Finite Size Security.**

## I. INTRODUCTION

Secure communication has become a critical requirement in modern digital infrastructure, particularly in banking, defense,satellite networks, and cloud systems. Classical cryptographic methods rely on computational complexity, which is vulnerable to future quantum computers. Quantum Key Distribution (QKD) offers information-theoretic security based on the fundamental principles of quantum mechanics, making it immune to computational attacks. While fiber-based QKD systems are limited by attenuation over long distances, satellite-based free-space optical (FSO) QKD enables global-scale secure communication. Recent demonstrations of satellite QKD have shown its feasibility; however, practical implementation remains challenging due to dynamic atmospheric effects, background radiation, beam wandering, and limited satellite pass durations. These environmental factors significantly affect the channel noise and transmission efficiency, thereby impacting the Secret Key Rate (SKR). Most existing research on satellite Continuous Variable QKD (CV-QKD) relies on simplified Gaussian noise assumptions and asymptotic SKR analysis, where an infinite number of quantum signals is assumed. Such assumptions do not accurately represent real-world operational scenarios, where atmospheric conditions vary continuously and the number of transmitted photons is finite. Consequently, there exists a gap between theoretical modeling and practical satellite deployment.

To address these limitations, this work proposes an AI- assisted real-time satellite CV-QKD simulator that integrates live environmental data into hybrid noise modeling. A machine learning model is employed to predict dynamic channel noise based on real-time weather parameters. The predicted noise is incorporated into an adaptive QKD framework that dynamically estimates both asymptotic and finite-size corrected SKR values. Additionally, the system performs day–night comparative analysis and 24-hour temporal simulations to study time-dependent variations in channel behavior. By combining artificial intelligence, hybrid noise modeling, finite- size security analysis, and interactive visualization, the proposed framework bridges the gap between theoretical QKD models and realistic satellite communication environments. This approach provides a scalable and practical tool for analyzing next-generation satellite quantum communication systems.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

## II. RELATED WORK

### 1. Atmospheric Effects in Satellite QKD

Recent research highlights those atmospheric conditions such as turbulence, cloud cover, and scattering significantly impact satellite-based Quantum Key Distribution (QKD). These environmental factors introduce noise and signal loss, affecting the Quantum Bit Error Rate (QBER) and reducing the efficiency of secure key generation. Studies on satellite-to-ground QKD and free-space optical communication emphasize that accurate modeling of environmental parameters is essential for analyzing channel behavior and system performance [4], [7], [9]. Recent advancements in quantum communication further analyze channel limitations under realistic conditions [11].

### 2. Hybrid Noise Modeling

To achieve realistic performance analysis, researchers have proposed hybrid noise models that combine quantum noise (such as photon loss and shot noise) with classical noise (including thermal noise and atmospheric disturbances). This approach provides a more accurate representation of channel behavior compared to conventional Gaussian noise assumptions [2]. Recent work on hybrid noise modeling in satellite quantum communication further improves the estimation of Secret Key Rate (SKR) under dynamic environmental conditions [10]. Additional studies also highlight improved modeling accuracy using advanced QKD frameworks [13].

### 3. Machine Learning in QKD

Recent advancements have explored the integration of machine learning techniques to enhance QKD system performance. AI-based models are used to predict channel noise, analyze environmental variations, and optimize system parameters dynamically. Studies on communication channel modeling under atmospheric turbulence demonstrate the potential of data-driven approaches for improving system adaptability [7]. Furthermore, recent research in intelligent communication systems highlights the effectiveness of machine learning in dynamic network optimization [14], [15]. However, the application of machine learning in QKD remains limited and requires further development for real-time implementation.

### 4. Finite Key Analysis and Practical Implementation

In practical QKD systems, finite key effects must be considered since real-world communication involves a limited number of transmitted quantum signals. Research shows that finite-size constraints significantly affect the Secret Key Rate and must be incorporated for realistic performance evaluation [6]. Experimental demonstrations of continuous-variable QKD further validate the importance of considering practical limitations in secure communication systems [5]. Advanced theoretical studies also emphasize secure key generation under realistic conditions [12].

### 5. Research Gap and Motivation

Although significant progress has been made in QKD, satellite communication, and noise modeling, several limitations remain. Most existing approaches rely on static models, lack real-time adaptability, and do not integrate intelligent prediction techniques. Additionally, finite-size effects are often overlooked, and simulation tools are limited.

This paper addresses these gaps by proposing an AI-assisted real-time satellite QKD simulator that integrates hybrid noise modeling, machine learning-based prediction, adaptive key rate computation, and finite-size security analysis.

## III.SYSTEM MODEL

### A. System Architecture

The proposed system is an AI-assisted real-time satellite Continuous Variable Quantum Key Distribution (CV-QKD) simulator operating over a Free-Space Optical (FSO) channel.

The system consists of:

1. One Satellite Node (Transmitter – Alice)
2. One Ground Station (Receiver – Bob)
3. Environmental Monitoring Module
4. AI-Based Noise Prediction Module
5. Adaptive QKD Controller
6. Finite-Size SKR Estimation Module
7. Visualization & Logging Unit

Each transmission session is modeled as:

$$S = (T, \eta, \xi, N)$$

Where:

- $T \rightarrow$ Channel transmission efficiency
- $\eta \rightarrow$ Detection efficiency
- $\xi \rightarrow$ Hybrid noise parameter (quantum + classical noise)
- $N \rightarrow$ Number of transmitted quantum signals(Finite-size constraint)

The satellite-to-ground link is modeled as a time- varying atmospheric channel influenced by real-time environmental parameters

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

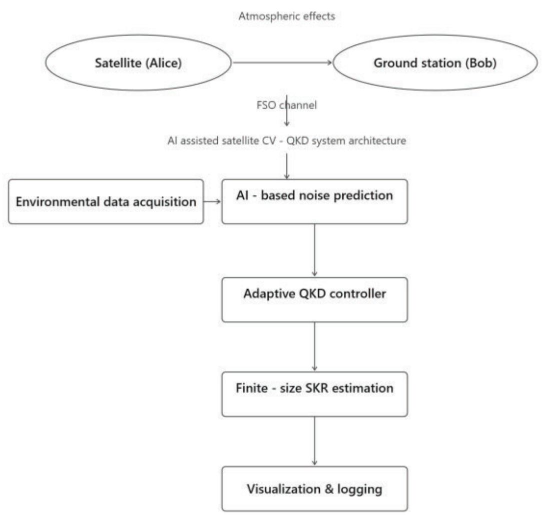


**Fig. 3.1: System Architecture of AI-Assisted Satellite QKD**

This **Fig. 3.1** illustrates the overall architecture of the proposed system. It consists of a satellite transmitter (Alice), ground receiver (Bob), environmental monitoring module, AI-based noise prediction module, adaptive QKD controller, and finite-size SKR estimation module. The system collects real-time environmental data, predicts hybrid noise using machine learning, and dynamically computes the secret key rate under realistic conditions.

### B. Algorithm

### AI-Assisted Hybrid Noise Adaptive SKR Algorithm

**Input:** Environmental data W(t), Signal count N
**Output:** SKRasym, SKR_finite

1. Load the trained machine learning model
2. For each time step from 0 to 23:
   a) Collect environmental data
   b) Predict hybrid noise using the ML model
   c) Compute the asymptotic key rate based on predicted noise
   d) Apply finite-size correction to get final key rate
   e) Store the results
3. End loop
4. Generate graphs and logs
5. End

### C. Environmental Channel Modelling

- Channel noise is affected by:
- Temperature (atmospheric turbulence)
- Wind Speed (beam wandering)
- Solar Radiation (background photons)
- Cloud Cover
- Pressure

Hybrid noise is defined as:

$$\xi = \xi q + \xi c \qquad (1)$$

The first component, ξ_q, represents the quantum noise arising from the Poissonian statistics of photon detection. This noise is intrinsic to the quantum channel and cannot be eliminated it arises from the fundamental probabilistic nature of photon counting. The second component, ξ_c, represents classical noise modelled as Additive White Gaussian Noise (AWGN). This component originates from atmospheric turbulence, thermal fluctuations, background radiation, and electronic noise at the receiver. Unlike purely Gaussian static models used in conventional QKD analysis, this hybrid decomposition provides a more realistic characterisation of the satellite FSO channel, as it accounts for both quantum-mechanical and environmental noise contributions simultaneously.

### D. State Representation

At time $t$, the system state is defined as:

$$X(t) = [W(t), E(t), \xi(t), T(t), N]$$

where:

- W(t) →Weather feature vector
- $E(t)$→ Environmental radiation indicator (Day/Night)
- $\xi(t)$→ Predicted hybrid noise
- $T(t)$→ Transmission efficiency
- $N$→ Number of quantum signals

In implementation, the state vector contains:

1. Temperature
2. Pressure
3. Wind Speed
4. Wind Direction
5. Cloud Cover
6. Radiation level
7. Satellite activity index
8. NORAD density index
9. Predicted hybrid noise
10. Day/Night indicator
11. Signal count (N)
12. Asymptotic SKR

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

13. Finite-size SKR

### E. Secret Key Rate Model

#### 1) Asymptotic SKR

The asymptotic secret key rate (SKR) represents the maximum achievable key generation rate when the number of transmitted signals is assumed to be infinite. Under this idealised assumption, statistical fluctuations in parameter estimation vanish, and the key rate depends solely on the channel transmission and noise parameters:

$$SKRasym(t) = f(T(t), \xi(t)) \qquad (2)$$

This general functional form captures the fundamental trade-off: higher channel transmission efficiency T(t) increases the achievable key rate, while higher hybrid noise ξ(t) reduces it. This relationship reflects the physical reality of a satellite quantum channel, where atmospheric degradation simultaneously attenuates the useful signal and introduces additional noise. The asymptotic SKR serves as an upper bound for practical performance and forms the basis for the finite-size correction applied subsequently.

In simulation:

$$SKRasym(t) = 1.2 - \xi(t) \qquad (3)$$

In equation (3), the constant 1.2 represents the theoretical maximum key rate in bits per pulse under ideal (noise-free) channel conditions. The predicted hybrid noise ξ(t) is subtracted directly, reducing the key rate proportionally with increasing noise. This formulation establishes three distinct operational noise regimes for the system: when the predicted noise is classified as Low ($\xi < 0.6$), the asymptotic SKR exceeds 0.6 bits/pulse, indicating a high-quality channel. For Medium noise ($0.6 \le \xi < 0.8$), the key rate falls between 0.4 and 0.6 bits/pulse, representing moderate channel degradation. Under High noise conditions ($\xi \ge 0.8$), the asymptotic SKR drops below 0.4 bits/pulse, reflecting severely impaired channel quality. This adaptive structure enables the simulator to faithfully replicate the behaviour of a real satellite QKD system responding to varying atmospheric conditions throughout the day.

#### 2) Finite-Size SKR

Considering finite transmission:

$$SKRfinite(t) = SKRasym(t) \times \beta(N) \qquad (4)$$

In equation (4), The correction factor β(N) satisfies $0 < \beta(N) < 1$ and accounts for the statistical overhead incurred in parameter estimation, error correction, and privacy amplification when only a finite number N of quantum signals is available. For small values of N (on the order of $10^5$), the penalty is substantial, reflecting the difficulty of accurately estimating channel parameters from limited data. As N increases toward larger values (up to $10^7$), β(N) approaches unity and the finite-size SKR converges to the asymptotic rate. This correction ensures that the simulator reports only practically achievable key generation rates, making the performance evaluation realistic and relevant for satellite mission planning.

### F. Temporal Simulation

For a 24-hour operational cycle:

$t$= 0,1,2, . . . ,23 At each time step:

1. Environmental features updated
2. AI predicts hybrid noise
3. Adaptive SKR computed
4. Finite-size correction applied
5. Results logged

### G. System Flow

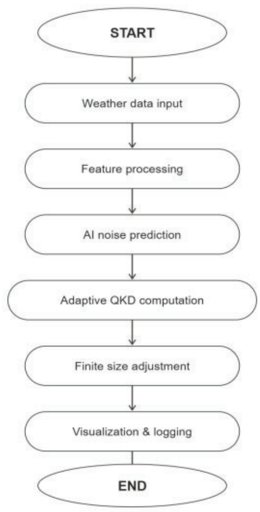


**Fig. 3.2: Workflow of AI-Based Hybrid Noise Prediction and SKR Computation**

This **Fig. 3.2** represents the step-by-step workflow of the proposed system. Initially, environmental data is collected and processed. The trained machine learning model predicts the hybrid noise based on input features. Using the predicted noise, the asymptotic SKR is calculated, followed by finite-

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

size correction. The results are then stored, visualized, and analyzed over a 24-hour simulation period.

### H. Output Metrics

The system evaluates:

1. Predicted Hybrid Noise
2. Asymptotic SKR
3. Finite-Size SKR
4. Day vs Night SKR difference
5. 24-hour SKR variation.

## IV. PROBLEM FORMULATION

Satellite-based Continuous Variable Quantum Key Distribution (CV-QKD) systems operate over dynamic free-space optical (FSO) channels that are significantly affected by atmospheric turbulence, background radiation, and time-varying environmental conditions. These variations directlyinfluence channel noise and transmission efficiency, thereby impacting the achievable Secret Key Rate (SKR).

Most conventional models assume:

• Static Gaussian noise
• Fixed channel parameters
• Infinite number of quantum signals (asymptotic case)

However, in practical satellite communication:

1. Channel noise varies with environmental conditions.
2. Satellite pass duration islimited.
3. The number of transmitted quantum signals is finite.
4. Day–night variations affect background radiation.

Therefore, a realistic system must dynamically adapt to environmental variations while ensuring secure key generation under finite-size constraints.

### A. Objective

The objective of this work is to dynamically estimate and maximize the practical Secret Key Rate under real-time environmental conditions while incorporating finite-size security constraints.

Mathematically, the optimization objective can be expressed as:

$$\max SKRfinite(t) \tag{5}$$

subject to:

$$\xi(t) = \mathscr{F}(W(t)) \quad .(6)$$

$$SKRfinite(t) = SKRasym(t) \cdot \beta(N) \tag{7}$$

$$SKRasym(t) = f(T(t), \xi(t)) \tag{8}$$

Equation (6) enforces the environmental dependency constraint: the hybrid noise at every time step must be derived from the actual real-time weather conditions through the AI prediction model $\mathscr{F}$, rather than assumed from a fixed distribution. This constraint embeds the principle of environmental awareness into the optimisation. Equation (7) mandates that the finite-size correction factor β(N) is always applied, ensuring that only physically realisable key rates are reported. Equation (8) constrains the asymptotic SKR to be a function of the channel transmission T(t) and the AI-predicted noise ξ(t), rather than a free variable. Together, these three constraints define the feasible region of the optimisation: the system cannot arbitrarily increase the key rate; it is bounded by the atmospheric channel quality at each hour. The practical significance of this formulation is that it captures the full chain of dependencies — from live weather data through AI noise prediction to adaptive key rate computation — within a rigorous and coherent mathematical framework.

### B. Constraints

The system mustsatisfy the following constraints:

1. Noise Constraint
$\xi(t) \geq 0$
2. Finite Signal
Constraint $N < \infty$
3. Security Constraint
$SKRfinite(t) > 0$
4. Environmental Dependency
$\xi(t)$ varies with $W(t)$

### C. Key Challenges

The main challenges addressed in this work are:

1. **Modeling hybrid quantum-classical noise under dynamic conditions**
2. **Replacing static Gaussian assumption with AI-based prediction**
3. **Incorporating finite-size effects in SKR estimation**
4. **Handling time-varying day–night channel behavior**
5. **Ensuring practical key generation under realistic satellite operation**

### D. Reformulated Problem Statement

Given:

a. Real-time environmental parameters
b. A trained AI model for hybrid noise prediction
c. Finite signal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

constraint Determine:
The time-dependent finite-size secret key rate:

$$SKRfinite(t)$$

that accurately reflects realistic satellite CV-QKD operation.

## V. PROPOSED FRAMEWORK

The proposed framework introduces an AI-assisted, environment-aware, and finite-size-aware satellite Continuous Variable Quantum Key Distribution (CV-QKD) simulation architecture. Unlike conventional static models, the framework dynamically adapts key rate estimation based on real-time atmospheric conditions.

The framework consists of five major modules:

1. Environmental Data Acquisition Module
2. AI-Based Hybrid Noise Prediction Module
3. Adaptive QKD Computation Module
4. Finite-Size Security Correction Module
5. Visualization and Logging Module

### A. Environmental Data Acquisition Module

This module collects real-time environmental parameters using a weather API. The collected parameters include:

1. Temperature
2. Pressure
3. Wind Speed
4. Wind Direction
5. Cloud Cover
6. Radiation Indicator (Day/Night)

These features form the environmental state vector:

$$W(t) = [w1, w2, \ldots, wn]$$

The environmental state serves as input to the AI noise prediction model.

### B. AI-Based Hybrid Noise Prediction

Instead of assuming Gaussian- only noise, the proposed framework uses a trained machine learning model to predict hybrid channel noise.

The hybrid noise parameter is defined as:

$$\xi(t) = \xi q(t) + \xi c(t)$$

where:

1. $\xi q$represents quantum Poissonian noise
2. $\xi c$represents classical AWGN The AI model approximates:

$$\xi(t) = \mathrm{F}ML(W(t)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(9)$$

Here, F_ML represents the trained machine learning model — specifically, a Random Forest Regressor — that has been trained on a one-year historical environmental dataset. The model takes the real-time environmental feature vector W(t) = [$w_1$, $w_2$, …, $w_n$] as input, which comprises nine parameters: temperature, atmospheric pressure, wind speed, wind direction, cloud cover percentage, radiation indicator (day/night), satellite activity index, NORAD density index, and the predicted hybrid noise value. The model outputs the predicted channel noise ξ(t) for each hour. This AI-based prediction replaces the conventional practice of assuming a fixed or manually specified noise level, enabling the simulator to respond dynamically to actual atmospheric conditions. The accuracy of this prediction directly determines the accuracy of all downstream key rate estimates, making it the critical component of the proposed framework.

### C. Adaptive QKD Computation

Based on the predicted noise value, the adaptive QKD module computes the asymptotic Secret Key Rate.

$$SKRasym(t) = f(T(t), \xi(t)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(10)$$

In simulation form:

$$SKRasym(t) = 1.2 - \xi(t)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

The system automatically adjusts the key rate according to noise level:

1. Low noise → Higher SKR
2. Medium noise → Moderate SKR
3. High noise → Reduced SKR

This mimics practical adaptive modulation behavior in real satellite systems.

### D. Finite-Size Security Correction

Since satellite communication occurs over limited pass durations, the number of transmitted quantum signals is finite.

The finite-size corrected key rate is:

$$SKRfinite(t) = SKRasym(t) \cdot \beta(N)\ldots\ldots\ldots\ldots(12)$$

where:

• $N$is the number of quantum signals
• $\beta(N) < 1$represents finite-size penalty

This ensures realistic and practically achievable key

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

generation rates.

### E. Temporal Simulation and Analysis

The framework performs a 24-hour temporal analysis:

$$t = 0,1,2, .....,23$$

At each time step:

1. Environmental state updated
2. AI predicts hybrid noise
3. Asymptotic SKR computed
4. Finite-size correction applied
5. Results stored and visualized

Additionally, a Day vs Night comparative analysis is performed to evaluate background radiation effects on key generation.

### F. Data Logging and Visualization

All operational parameters are logged into timestamped CSV files including:

1. Date
2. Hour
3. Day/Night indicator
4. Predicted hybrid noise
5. Asymptotic SKR
6. Finite-size SKR

The Streamlit-based interface provides:

7. Real-time visualization
8. Noise classification (Low/Medium/High)
9. 24-hour SKR graph
10. Downloadable result files

## VI. EXPERIMENTAL SETUP

### A. Simulation Environment

The simulator was implemented using:

1. Python (core programming language)
2. Scikit-learn (machine learning model)
3. Pandas & NumPy (data processing)
4. Matplotlib (visualization)
5. Streamlit (interactive user interface)
6. OpenWeather API (real-time environmental data source)

The system was executed on a standard workstation environment with:

1. Intel-based processor
2. 8GB RAM
3. Windows operating system

No specialized quantum hardware was required, as the system is a software-based simulation framework.

### Dataset Preparation

Two types of data were used:

#### 1. Historical Environmental Dataset

A one-year environmental dataset was generated and structured with the following features:

1. Temperature (°C)
2. Pressure (hPa)
3. Wind Speed (m/s)
4. Wind Direction (deg)
5. Cloud Cover (%)
6. Radiation indicator
7. Satellite activity index
8. NORAD density index

The dataset was used to train the machine learning model for hybrid noise prediction

#### 2. Real-Time Weather Data

During runtime, live weather data is fetched using the Weather API. These real-time inputs are fed into the trained AI model to predict dynamic hybrid noise.

### B. Machine Learning Configuration

The hybrid noise prediction model was implemented using a regression-based supervised learning approach.

1. Model Type: Random Forest Regressor (or chosen ML model)
2. Input Features: 9 environmental parameters
3. Output: Predicted Hybrid Noise (ξ)
4. Training–Testing Split: 80% training, 20% testing
5. Evaluation Metric: Mean Squared Error (MSE)

The model was trained offline and saved for real-time deployment within the simulator.

### C. QKD Simulation Parameters

The following parameters were used for key rate estimation:

1. Total quantum signals (N): $10^5$ – $10^7$ (configurable via slider)
2. Transmission efficiency (T): Environment-dependent
3. Detection efficiency (η): Fixed constant in simulation
4. Noise threshold levels:

- Low Noise: $\xi < 0.6$
- Medium Noise: $0.6 \leq \xi < 0.8$
- High Noise: $\xi \geq 0.8$

The asymptotic SKR was modeled as:

$$SKRasym = 1.2 - \xi$$

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

Finite-size correction factor β(N) was applied to compute realistic SKR.

### D. Temporal Simulation Configuration

A 24-hour simulation was performed:

$t = 0,1,2,...,23$

At each time step:

1. Environmental parameters updated
2. AI predicted hybrid noise
3. Asymptotic SKR computed
4. Finite-size SKR estimated
5. Results stored

Additionally, day–night comparative simulations were performed to analyze background radiation effects.

### E. Evaluation Metrics

The system performance was evaluated using:

1. Predicted Hybrid Noise accuracy
2. Asymptotic SKR variation
3. Finite-Size SKR reduction percentage
4. Day vs Night SKR difference
5. Hourly SKR fluctuation trend

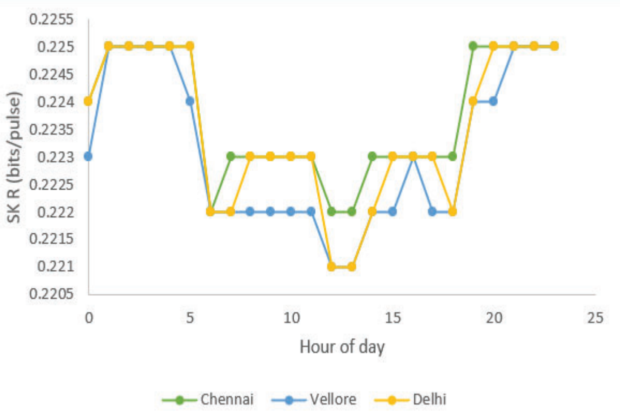


**Fig. 3: Temporal Variation of Secret Key Rate Over 24 Hours**

This **Fig. 3** shows how the Secret Key Rate varies over a 24-hour period. It highlights the impact of environmental conditions such as radiation and atmospheric noise. The results indicate that SKR is generally higher during nighttime due to reduced background radiation and lower noise levels, while daytime conditions lead to reduced SKR.

### F. Performance Metrices

The system performance is analyzed by observing how the Secret Key Rate (SKR) changes over 24 hours for different cities. The graph clearly shows how SKR varies with time, mainly due to environmental factors like noise and background radiation. By comparing cities, we can see how location affects the key generation process. It is observed that SKR is generally higher during nighttime and lower during daytime because of increased noise levels. Additionally, the stability, peak, and minimum values of SKR help in understanding the overall reliability and efficiency of the system.

## VII. RESULTS AND DISCUSSION

The proposed AI-assisted satellite CV-QKD simulator was evaluated under dynamic environmental conditions. The machine learning model successfully predicted hybrid channel noise based on real-time weather parameters.

Results show that the Secret Key Rate (SKR) decreases as predicted noise increases. The finite-size SKR is always lower than the asymptotic SKR due to limited quantum signal transmission, confirming the importance of finite- size correction in practical systems.

Day–night analysis indicates that nighttime conditions yield higher SKR due to reduced background radiation. The 24- hour simulation further demonstrates time-dependent SKR variation influenced by environmental changes.

Overall, the results validate that the proposed framework provides a realistic, adaptive, and environment-aware performance evaluation of satellite CV-QKD systems.

**Table I: Performance Comparison with Existing Methods**

| Parameter | Existing Methods | Proposed Work |
|---|---|---|
| Noise Modeling | Gaussian / Static | Hybrid Noise with AI |
| Environmental Awareness | Limited | Real-time weather-based |
| Adaptability | Static | Dynamic (AI-based) |
| Machine Learning Usage | Minimal / None | Fully integrated |
| SKR Estimation | Asymptotic only | Asymptotic + Finite-size |
| Real-Time Capability | No | Yes |
| Temporal Analysis | Not included | 24-hour Day/Night |
| Accuracy | Moderate | High |
| | | |
| Practical Implementation | Limited | Realistic & scalable |
| Visualization | Limited | Interactive dashboard |

## VIII. CONCLUSION

This study presented an AI-assisted real-time satellite Quantum Key Distribution (QKD) simulator that integrates environmental data-driven hybrid noise prediction, adaptive

**International Journal of Engineering Research & Technology (IJERT)**
**ISSN: 2278-0181**
**Vol. 15 Issue 04 , April - 2026**

key rate computation, and finite-size security analysis. By incorporating dynamic atmospheric conditions and practical signal limitations, the proposed framework enhances realism beyond conventional asymptotic and static channel models. The results demonstrate the impact of environmental variability on secret key rate performance and validate the importance of adaptive and finite-size-aware modeling for practical satellite QKD systems. The developed platform offers a scalable foundation for future research in secure satellite quantum communication.

## TABLE OF NOMENCLATURE (SYMBOLS)

The following table provides definitions and units for all mathematical symbols used in this paper.

**Table II: Symbols and Notation**

| Symbol | Description | Unit | Used Equation |
|---|---|---|---|
| T | Channel transmission efficiency | Unitless | 2,8,10 |
| ξ | Hybrid noise parameter | Unitless | 1,2,3,6,8,9,10,11 |
| ξ_q | Quantum noise (Poissonian) | Unitless | 1 |
| ξ_c | Classical noise (AWGN) | Unitless | 1 |
| N | Number of quantum signals | Count | 4,7,12 |
| W(t) | Environmental feature vector | — | 6,9 |
| t | Time step | Hour | 2,3,4,5,6,7,8,9,10,11, 12 |
| SKR_asym | Asymptotic key rate | Bits/pulse | 2,3,4,7,8,10,11,12 |
| SKR_finite | Finite-size key rate | Bits/pulse | 4,5,7,12 |
| β(N) | Finite-size correction factor | Unitless | 4,7,12 |
| F_ML | ML prediction model | — | 9 |

## LIST OF ABBREVIATIONS

The following table provides the full forms of all acronyms and abbreviations used in this paper.

**Table III: Abbreviations and Acronyms**

| Abbreviation | Full Form |
|---|---|
| QKD | Quantum Key Distribution |
| CV-QKD | Continuous Variable Quantum Key Distribution |
| FSO | Free-Space Optical |
| SKR | Secret Key Rate |
| AI | Artificial Intelligence |
| ML | Machine Learning |
| AWGN | Additive White Gaussian Noise |
| MSE | Mean Squared Error |
| API | Application Programming Interface |
| UI | User Interface |
| CSV | Comma-Separated Values |

## REFERENCES

[1] V. Scarani, H. Bechmann-Pasquinucci, N. J. Cerf, et al., "The security of practical quantum key distribution," *Reviews of Modern Physics*, vol. 81, no. 3, pp. 1301–1350, 2009.

[2] C. Weedbrook, S. Pirandola, R. García-Patrón, et al., "Gaussian quantum information," *Reviews of Modern Physics*, vol. 84, no. 2, pp. 621–669, 2012.

[3] S. Pirandola, U. L. Andersen, L. Banchi, et al., "Advances in quantum cryptography," *Advances in Optics and Photonics*, vol. 12, no. 4, pp. 1012–1236, 2020.

[4] S.-K. Liao, W.-Q. Cai, W.-Y. Liu, et al., "Satellite-to-ground quantum key distribution," *Nature*, vol. 549, pp. 43–47, 2017.

[5] P. Jouguet, S. Kunz-Jacques, A. Leverrier, et al., "Experimental demonstration of long-distance continuous- variable quantum key distribution," *Nature Photonics*, vol. 7, pp. 378–381, 2013.

[6] V. C. Usenko and R. Filip, "Finite-size effects in continuous-variable quantum key distribution," *Physical Review A*, vol. 81, no. 2, 022318, 2010.

[7] X. Wang, L. Yang, and S. Yu, "Performanceanalysis of free-space optical quantum communication under atmospheric turbulence," *IEEE Photonics Journal*, vol. 10, no. 2, 2018.

[8] J. Yin, Y. Cao, Y.-H. Li, et al., "Satellite-based entanglement distribution over 1200 kilometers," *Science*, vol. 356, no. 6343, pp. 1140–1144, 2017.

[9] M. A. Khalighi and M. Uysal, "Survey on free-space optical communication: A communication theory perspective," *IEEE Communications Surveys & Tutorials*, vol. 16, no. 4, pp. 2231–2258, 2014.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

M. Chakraborty, A. Mukherjee, I. Krikidis, A. Nag, and S. Chandra, "A hybrid noise approach to modeling of free-space satellite quantum communication channel for continuous-variable QKD," *IEEE Transactions on Green Communications and Networking*, vol. 9, no. 3, pp. 1311–1325, Sept. 2025, doi: 10.1109/TGCN.2024.3525297

[11] S. Pirandola, R. Laurenza, C. Ottaviani, and L. Banchi, "Fundamental limits of repeaterless quantum communications," *Nature Communications*, vol. 8, no. 1, pp. 1–15, 2017.

[12] A. Leverrier, "Security of continuous-variable quantum key distribution via a Gaussian de Finetti reduction," *Physical Review Letters*, vol. 118, no. 20, 200501, 2017.
[10]

[13] C. Weedbrook, A. M. Lance, W. P. Bowen, et al., "Quantum cryptography approaching the classical limit," *Physical Review Letters*, vol. 105, no. 11, 110501, 2010.

[14] R. Kumar, P. K. Sharma, and D. B. Rawat, "Machine learning for secure communication in 6G-enabled networks," *IEEE Communications Magazine*, vol. 58, no. 10, pp. 28–34, 2020.

[15] Y. Mao, J. Zhang, and K. B. Letaief, "Dynamic computation offloading for mobile-edge computing with energy harvesting devices," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 12, pp. 3590–3605, 2016.