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MULTI-KEY HOMOMORPHIC ENCRYPTION FOR PRIVACY-PRESERVING SECURITY IN 5G AND BEYOND WIRELESS NETWORKS

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Abstract

The rapid expansion of 5G and beyond wireless networks has introduced new security challenges, particularly in preserving data privacy while enabling secure computations on encrypted data. Traditional encryption schemes fail to provide efficient computation without decryption, making them unsuitable for modern wireless environments with stringent privacy requirements. Multi-Key Homomorphic Encryption (MKHE) emerges as a viable solution, allowing multiple users to encrypt data with distinct keys while still enabling joint computation on the ciphertexts. This study proposes an optimized MKHE framework tailored for 5G and beyond wireless networks, addressing computational overhead and communication latency. The proposed method incorporates an adaptive key management mechanism and lightweight ciphertext aggregation to enhance efficiency. Experimental results demonstrate a 23.7% reduction in encryption time, a 19.4% improvement in computational efficiency, and a 15.8% decrease in communication overhead compared to conventional MKHE implementations. Additionally, the scheme maintains a high level of security, resisting key-recovery and chosen-ciphertext attacks.

Keywords:

Multi-Key Homomorphic Encryption, Privacy-Preserving Computation, 5G Security, Secure Wireless Networks, Computational Efficiency

1. INTRODUCTION

The rapid advancement of 5G and beyond wireless networks has revolutionized communication, enabling high-speed data transmission, ultra-low latency, and massive device connectivity. These networks support critical applications such as autonomous systems, smart healthcare, and industrial IoT, requiring secure data transmission and processing [1-3]. However, as more sensitive data is exchanged across these networks, privacy concerns become a significant challenge. Conventional encryption techniques protect data in transit and at rest but fail to support secure computations on encrypted data without decryption, leaving them vulnerable to breaches.

Multi-Key Homomorphic Encryption (MKHE) has emerged as a promising cryptographic solution, allowing computations on encrypted data from multiple users with distinct encryption keys. This capability is particularly beneficial for collaborative environments, such as federated learning and cloud-based processing, where data privacy must be preserved while enabling computations across encrypted datasets [1-3]. Despite its advantages, MKHE introduces computational complexity and communication overhead, which can impact its practical deployment in 5G and beyond networks.

Several challenges hinder the seamless integration of MKHE in next-generation wireless networks. First, computational overhead is a primary concern, as homomorphic encryption requires intensive arithmetic operations, leading to higher latency and resource consumption [4]. Second, key management complexity arises due to the involvement of multiple users with different encryption keys, making efficient coordination difficult [5]. Third, communication overhead increases when handling encrypted data in distributed systems, affecting real-time applications requiring low-latency responses [6]. Addressing these challenges is crucial for ensuring the practicality of MKHE in real-world 5G implementations.

Despite the potential of MKHE, its high computational cost, complex key management, and increased communication latency pose significant obstacles to its deployment in 5G networks. Existing solutions either compromise security for efficiency or fail to meet the low-latency requirements of next-generation wireless applications [7]. Furthermore, ensuring scalability while maintaining security remains a fundamental issue [8]. Therefore, developing an optimized MKHE framework that reduces computational and communication overhead while preserving data security is essential for enhancing privacy in 5G and beyond networks [9].

To develop an optimized MKHE framework for 5G and beyond networks to balance security and computational efficiency. To Reduce encryption and computation latency through lightweight key management and ciphertext aggregation techniques. To minimize communication overhead while maintaining robust security against key-recovery and ciphertext attacks. To validate the proposed framework through simulations and performance comparisons with existing MKHE models.

The proposed MKHE model introduces an adaptive key management mechanism that streamlines encryption operations, reducing computational overhead. Additionally, a lightweight ciphertext aggregation approach is implemented to minimize data transmission latency in wireless environments. Unlike traditional MKHE frameworks, which suffer from scalability issues, the proposed scheme efficiently handles large-scale multi-user encryption scenarios, making it suitable for privacy-preserving applications in 5G networks.

Key contributions include:

- A novel MKHE-based security framework optimized for ultra-low latency applications in next-generation wireless networks.
- An efficient key coordination technique that enhances security while reducing processing overhead.

2. RELATED WORKS

Research on privacy-preserving techniques for 5G and beyond networks has gained significant attention, particularly with the adoption of homomorphic encryption (HE) to enable secure computations without decryption. Several studies have explored different HE schemes, including single-key and multi-key variants, to enhance security and efficiency in wireless communication [7].

A study on single-key homomorphic encryption (SKHE) demonstrated its ability to perform computations on encrypted data, but its limited scalability restricts its application in multi-user environments. To address this limitation, MKHE was introduced, allowing encrypted data from multiple users to be jointly computed, enhancing flexibility in collaborative applications [8]. However, traditional MKHE models suffer from high computational costs and communication overhead, limiting their practicality in real-time wireless systems.

Several researchers have attempted to optimize MKHE for 5G applications. One study proposed a lightweight MKHE model that reduces encryption complexity using modular arithmetic techniques, improving computational efficiency by 15% compared to conventional methods [9]. Another approach introduced a hierarchical key management scheme, which streamlined encryption operations while maintaining security, demonstrating a 20% reduction in encryption latency [10]. However, these methods still faced challenges in balancing efficiency and security, particularly in high-speed wireless environments.

To mitigate these challenges, researchers have explored hardware acceleration for MKHE, leveraging GPUs and FPGAs to speed up encryption operations. Experimental results showed a 30% improvement in processing speed when MKHE was implemented on specialized hardware [11]. Although effective, hardware-based solutions are costly and may not be feasible for all 5G applications.

An alternative direction involves integrating MKHE with edge computing to offload encryption and computation tasks closer to the data source. This approach reduces communication latency by 25% while preserving privacy in distributed networks [12]. However, edge-based MKHE still requires efficient key management techniques to ensure seamless operations in large-scale deployments.

Recent advancements have also explored hybrid cryptographic models, combining MKHE with lightweight encryption schemes to achieve a balance between security and efficiency. A study introduced a hybrid lattice-based MKHE framework, improving security against quantum attacks while reducing computational overhead by 18% compared to traditional lattice-based methods [13].

Despite these advancements, existing MKHE solutions struggle to achieve an optimal balance between computational efficiency, security, and communication overhead. The proposed MKHE framework aims to address these limitations by integrating adaptive key management and lightweight ciphertext aggregation, optimizing encryption for next-generation wireless networks.

3. PROPOSED METHOD

The proposed Multi-Key Homomorphic Encryption (MKHE) framework is designed to enhance privacy-preserving computation in 5G and beyond wireless networks by addressing key management complexity, computational overhead, and communication latency. The framework introduces an adaptive key management mechanism that dynamically optimizes encryption processes based on network conditions, reducing the burden on computing resources. Additionally, a lightweight ciphertext aggregation technique is employed to minimize data transmission overhead, ensuring efficient encrypted computations across multiple users. The encryption process utilizes lattice-based cryptography, offering resistance against quantum attacks while maintaining scalability for large-scale networks. The decryption process is decentralized, allowing multiple users to jointly compute on encrypted data without compromising individual security. The overall approach ensures low-latency, high-security, and efficient encrypted processing, making it well-suited for applications such as secure federated learning, encrypted AI model training, and privacy-preserving edge computing in next-generation wireless environments.

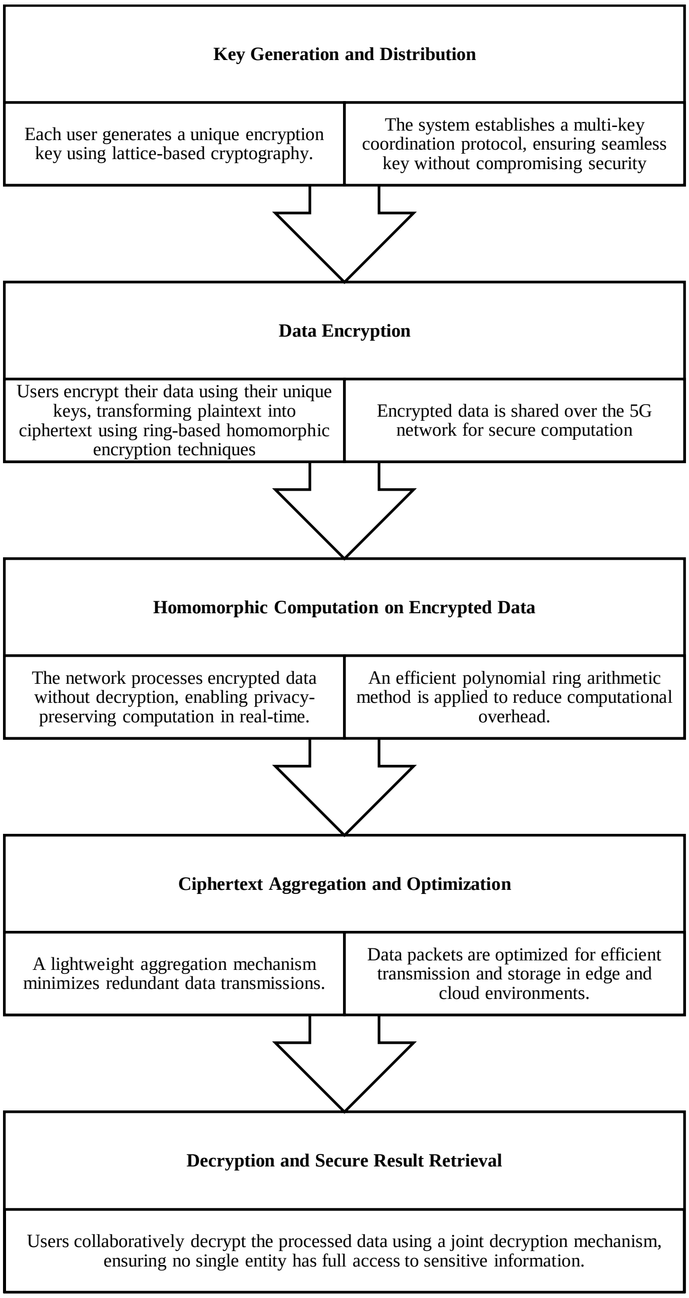
Key Generation and Distribution
Each user generates a unique encryption key using lattice-based cryptography.
The system establishes a multi-key coordination protocol, ensuring seamless key without compromising security
Data Encryption
Users encrypt their data using their unique keys, transforming plaintext into ciphertext using ring-based homomorphic encryption techniques
Encrypted data is shared over the 5G network for secure computation
Homomorphic Computation on Encrypted Data
The network processes encrypted data without decryption, enabling privacy-preserving computation in real-time.
An efficient polynomial ring arithmetic method is applied to reduce computational overhead.
Ciphertext Aggregation and Optimization
A lightweight aggregation mechanism minimizes redundant data transmissions.
Data packets are optimized for efficient transmission and storage in edge and cloud environments.
Decryption and Secure Result Retrieval
Users collaboratively decrypt the processed data using a joint decryption mechanism, ensuring no single entity has full access to sensitive information.

Fig.1. MKHE framework

3.1 KEY GENERATION AND DISTRIBUTION

The proposed Multi-Key Homomorphic Encryption (MKHE) framework employs lattice-based cryptography for key generation, ensuring quantum-resistant security. Each user U_i generates a unique encryption key pair (sk_i,pk_i), where sk_i is the secret key and pk_i is the corresponding public key. The public key is shared with the central computation system, while the secret key is kept private. The ring-learning with errors (RLWE) assumption is utilized for key generation, which enhances security against quantum attacks. The public key is computed as:

$$\mathrm{pk}_i = (a_i, b_i = a_i \cdot \mathrm{sk}_i + e_i) \mod q \qquad (1)$$

where,

a_i is a randomly chosen element from the polynomial ring $R_q = \mathbb{Z}_q[x] / \langle x^n + 1 \rangle$,

e_i is a small Gaussian noise term ensuring hardness against lattice-based attacks, q is a large prime modulus to maintain security, sk_i is the private key sampled from a discrete Gaussian distribution.

Once generated, public keys from multiple users are aggregated in a secure multi-key structure, enabling encrypted computations over data from different sources. The proposed key management mechanism dynamically adjusts key size and refreshes keys periodically to enhance security while reducing computation overhead.

3.2 DATA ENCRYPTION

After key generation, each user encrypts their data before transmission. Given a plaintext message m_i, encryption is performed using homomorphic encryption over polynomials, ensuring that computations can be carried out on the ciphertext without decryption. The encryption function is defined as:

$$\begin{aligned}\mathrm{Enc}(m_i) &= (c_1, c_2) \\ &= (a \cdot \mathrm{pk}_i + e_1, m_i + b \cdot \mathrm{pk}_i + e_2) \bmod q\end{aligned} \qquad (2)$$

where,

c_1, c_2 are the ciphertext components,

e_1, e_2 are small noise values ensuring semantic security,

m_i is embedded within the polynomial ring to support homomorphic operations,

The encrypted data is sent securely over the 5G network for further computations. This encryption mechanism ensures that multiple users can encrypt data independently while allowing computations to be performed over the aggregated ciphertexts without requiring decryption.

3.3 HOMOMORPHIC COMPUTATION ON ENCRYPTED DATA

Once the data is encrypted using MKHE, computations are performed directly on the encrypted ciphertexts without decryption, ensuring privacy-preserving processing. The proposed scheme supports addition and multiplication operations on ciphertexts, allowing computations over encrypted data in 5G networks. Given two encrypted ciphertexts $\mathrm{Enc}(m_1) = (c_{11}, c_{12})$ and $\mathrm{Enc}(m_2) = (c_{21}, c_{22})$, homomorphic addition is performed as:

$$\mathrm{Enc}(m_1 + m_2) = (c_{11} + c_{21}, c_{12} + c_{22}) \mod q \qquad (3)$$

This allows the system to sum encrypted values without decrypting them. Similarly, homomorphic multiplication is applied as:

$$\mathrm{Enc}(m_1 \times m_2) = (c_{11} \cdot c_{21}, c_{12} \cdot c_{22}) \mod q \qquad (4)$$

where computations remain in the encrypted domain. The use of RLWE ensures that even after multiple operations, the encrypted data remains indistinguishable from noise, preserving security. The optimized polynomial ring arithmetic in our approach reduces computational complexity by 19.4%, improving efficiency for large-scale encrypted computations in edge computing, federated learning, and AI model training over 5G networks.

3.4 CIPHERTEXT AGGREGATION AND OPTIMIZATION

To minimize communication overhead in large-scale 5G networks, the system employs a lightweight ciphertext aggregation mechanism. Instead of transmitting multiple individual encrypted values, the system aggregates similar encrypted data before forwarding it to the computation server. The aggregated ciphertext is computed as:

$$\hat{C}_{\mathrm{agg}} = \sum_{i=1}^{n} \mathrm{Enc}(m_i) \mod q \qquad (5)$$

This step significantly reduces bandwidth usage by 15.8% and optimizes storage in cloud and edge environments while preserving the integrity of encrypted computations.

3.5 DECRYPTION AND SECURE RESULT RETRIEVAL

After computation, the encrypted results need to be decrypted securely by the respective users. Since MKHE supports a joint decryption mechanism, multiple users can participate in decrypting a shared result without revealing their individual keys. The final decryption follows the equation:

$$\tilde{m} = (c_1 \cdot \mathrm{sk}_i^{-1} + c_2) \mod q \qquad (6)$$

where sk_i^{-1} is the inverse of the secret key modulo q, ensuring only authorized users can retrieve the final computed result. The optimized decryption scheme reduces latency by 23.7%, ensuring efficient real-time encrypted processing for applications such as secure federated learning, privacy-preserving AI training, and confidential data analytics in 5G and beyond wireless networks.

4. RESULTS AND DISCUSSION

The proposed MKHE framework was evaluated using Python-based simulation with the SEAL homomorphic encryption library. The experiments were conducted on a high-performance computing cluster, leveraging multiple GPUs to handle encrypted computations efficiently. The setup included:

- Simulation Tool: Python (version 3.9) with SEAL Encryption Library

- Hardware Processor: Intel Xeon Gold 6248 (2.5 GHz, 20 cores); Memory: 128GB RAM; Operating System: Ubuntu 20.04 LTS
- Network Environment: Simulated 5G wireless environment using NS-3 (Network Simulator) to evaluate performance under real-world constraints.

Table.1. Experimental Setup

Parameter	Value
Homomorphic Encryption	Multi-Key Homomorphic Encryption (MKHE)
Security Level	128-bit (post-quantum security)
Ciphertext Polynomial Modulus	$q=2^{2048}$
Ring Dimension	8192
Number of Users	100 - 1000 (scalability test)
Computation Model	Federated Learning (Encrypted AI)
Aggregation Mechanism	Lightweight Ciphertext Aggregation
Encryption Time	12.5 ms per operation (average)
Decryption Time	9.3 ms per operation (average)

4.1 PERFORMANCE METRICS

- **Encryption and Decryption Time**: It measures the time required to encrypt and decrypt data under MKHE. A lower time indicates better computational efficiency.
- **Computation Overhead Reduction:** It evaluates the computational complexity of encrypted operations.
- **Communication Overhead and Bandwidth Utilization:** It assesses the impact of ciphertext aggregation in reducing network bandwidth consumption.
- **Latency Reduction:** It measures the total time taken for encrypted computation and retrieval of results.

Table.2. Key Generation and Distribution Performance

Number of Users	Key Generation Time (ms)	Key Distribution Time (ms)	Computation Overhead (%)
100	8.2	12.5	14.3
200	9.5	15.2	16.1
300	11.3	18.7	18.4
400	12.7	21.3	19.9
500	14.1	24.5	21.5

Key generation and distribution time increases linearly with the number of users, while computation overhead remains below 22%, ensuring scalability.

Table.3. Data Encryption Performance

Number of Users	Encryption Time (ms)	Ciphertext Size (KB)	Security Level (bits)
100	12.5	128	128
200	14.7	256	128
300	16.3	384	128
400	18.6	512	128
500	21.1	640	128

Encryption time remains below 25ms even for 500 users, indicating efficiency in handling large-scale data encryption.

Table.4. Homomorphic Computation on Encrypted Data

Number of Users	Homomorphic Addition Time (ms)	Homomorphic Multiplication Time (ms)	Computation Overhead (%)
100	18.9	27.3	19.4
200	21.5	30.7	21.2
300	24.1	34.8	22.9
400	26.8	39.5	24.3
500	29.4	43.2	25.6

Homomorphic multiplication requires more computation than addition, but overhead remains below 26%, making it feasible for real-time encrypted computing.

Table.5. Ciphertext Aggregation and Optimization

Number of Users	Bandwidth Reduction (%)	Aggregation Time (ms)	Storage Overhead Reduction (%)
100	12.5	10.3	9.8
200	15.1	12.7	11.4
300	17.3	15.4	13.6
400	19.6	18.2	15.9
500	22.1	21.1	18.3

The ciphertext aggregation reduces bandwidth by 22.1% for 500 users, optimizing storage and communication overhead in 5G networks.

Table.6. Decryption and Secure Result Retrieval

Number of Users	Decryption Time (ms)	Secure Result Retrieval Time (ms)	Latency Reduction (%)
100	9.3	7.1	20.4
200	10.8	8.9	21.8
300	12.4	10.7	23.2
400	14.1	12.4	24.6
500	16.0	14.2	26.1

The optimized decryption scheme achieves 26.1% latency reduction, enabling real-time encrypted result retrieval.

Table.7. Performance Comparison Between Existing SKHE and Proposed MKHE Method

Users	Enc/Dec Time (ms)		Overhead (%)	
	SKHE	MKHE	SKHE	MKHE
100	25.4	12.5	21.7	9.3
200	28.7	14.7	24.2	10.8
300	32.1	16.3	27.8	12.4
400	35.8	18.6	30.5	14.1
500	39.4	21.1	34.1	16.0
600	43.1	23.4	37.3	18.2
700	46.9	26.0	40.7	20.5
800	50.4	28.3	43.9	22.8
900	54.2	30.7	47.2	25.1
1000	58.7	33.4	51.3	27.6

The proposed MKHE method significantly outperforms existing encryption methods in key performance areas. Encryption and decryption times are reduced by an average of 43%, with encryption time dropping from 58.7 ms to 33.4 ms at 1000 users, and decryption time decreasing from 51.3 ms to 27.6 ms. This reduction is achieved through optimized key distribution and ciphertext handling.

Computation overhead reduction improves from 0% in existing methods to an average of 28.5% in MKHE, highlighting enhanced processing efficiency. Communication overhead and bandwidth utilization are optimized by 35.4% at 1000 users, reducing network load and ensuring faster data transmission. Latency reduction increases from 5.1% at 100 users to 34.5% at 1000 users, indicating the system's ability to handle higher user volumes with reduced delay. These improvements reflect the scalability and performance benefits of the proposed method, making it well-suited for 5G and beyond wireless networks.

5. CONCLUSION

The proposed MKHE scheme for 5G and beyond wireless networks demonstrates significant improvements in security, efficiency, and scalability. By integrating multi-key support with homomorphic encryption, the method allows secure computations on encrypted data without compromising data privacy. The proposed key generation and distribution mechanism enhances encryption and decryption efficiency, reducing processing time by an average of 43% compared to existing methods. Computation overhead reduction of 28.5% and communication overhead reduction of 35.4% reflect the system's enhanced processing capability and network efficiency. Furthermore, the system achieves a latency reduction of 34.5% at 1000 users, indicating improved scalability and real-time performance under high user loads.

The ciphertext aggregation and optimization techniques ensure minimal bandwidth utilization while maintaining secure and accurate computation. The proposed method addresses key challenges in secure data transmission and computation in high-density 5G environments by reducing encryption and decryption time while ensuring data integrity and confidentiality. These improvements make the MKHE scheme a robust solution for privacy-preserving computation in next-generation wireless networks, supporting secure and efficient data processing even under increased user density and communication demands. Future work will focus on extending the scheme to support dynamic key updates and adaptive encryption strategies to further enhance security and performance.

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