

A Novel Dynamic Shuffling and Secure Encryption Framework for Maximizing Data Availability without Compromising Data Privacy

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Abstract - The rapid expansion of cloud computing, smart devices, and large-scale data ecosystems has intensified the demand for robust data protection mechanisms that can balance both high availability and strong privacy preservation. Traditional encryption-heavy models introduce computational overhead and create trade-offs between usability and security. This research proposes an enhanced data protection architecture integrating Dynamic Shuffling (DS), Secret-Shared Dynamic Shuffling (SSDS), and a Secure Encryption Model (SEM) based on Hadamard transforms. These lightweight mechanisms aim to improve confusion, diffusion, and resistance to cryptographic attacks while maintaining low processing overhead and high data availability. The paper presents the proposed system's design, evaluates its security properties, compares performance against conventional ECC-based systems, and highlights its efficiency in secure transmission, storage, and authentication. Results show that the model significantly reduces storage cost, improves execution time, and strengthens resistance to attacks, demonstrating promise for cloud security applications.

Keywords: Data Privacy Preservation, Dynamic Shuffling Mechanism, Cloud Data Security, High Data Availability, Lightweight Encryption Techniques

1. INTRODUCTION

Modern cloud-based infrastructures rely on massive data exchange between user devices and cloud storage providers. With billions of smart devices operating under constraints such as limited memory, computational power, and battery life, lightweight yet secure protection mechanisms are crucial. Ensuring data availability while preserving privacy is increasingly difficult due to vulnerabilities in key management, algorithmic implementations, and side-channel attacks prevalent in existing encryption systems.

The security challenges include:

- high computational overhead of encryption algorithms,
- vulnerability of keys stored or transmitted insecurely,
- risks of Cross-VM attacks,
- man-in-the-middle, replay, and credential-based attacks,
- predictable operations in traditional fixed shuffling techniques.

To overcome these limitations, the proposed research introduces a **new multi-layered security framework** comprising dynamic shuffling, key-splitting, and multi-round Hadamard-based encryption to achieve **maximized data availability without compromising privacy**.

2. RELATED WORK

Existing research highlights the limitations of traditional encryption and key management mechanisms. Studies on homomorphic encryption, differential privacy, secret sharing schemes, and cloud auditing emphasize the need for balance between usability and protection. However, most methods incur heavy computation, making them unsuitable for resource-constrained environments.

Shuffling techniques, permutation ciphers, and lightweight data transformation mechanisms have gained attention for reducing overhead while enhancing diffusion. Recent cloud security frameworks suggest hybrid models that integrate lightweight methods

with selective encryption to address efficiency issues. The proposed research builds on these approaches, combining **dynamic shuffling + shared keys + multi-round transformations** for improved resilience and performance.

Mohamed Azharudheen, Kumudham, and Kalaivani [6] propose a scalable deep learning–optimized architecture designed to strengthen data security while maintaining high availability in big data ecosystems. Their work addresses the limitations of traditional encryption and anomaly detection systems, which often fail to operate efficiently under large-scale, distributed workloads. Recognizing that deep learning models demand substantial computational resources and that security mechanisms can easily become performance bottlenecks, the authors introduce an integrated framework that combines dynamic data transformation, intelligent threat detection, and lightweight cryptographic operations. Their approach is particularly effective in high-throughput environments where rapid decision-making and uninterrupted data access are essential. By optimizing security processes through deep learning and scalable data pipelines, the study demonstrates that it is possible to achieve robust protection without degrading system performance—a key requirement for next-generation cloud and big-data infrastructures.

Mohamed Azharudheen and Vijayalakshmi [8] investigate a novel data protection mechanism aimed at maximizing data availability while ensuring strong privacy preservation in large-scale cloud environments. Their work emphasizes the limitations of traditional cryptographic approaches, particularly in scenarios involving resource-constrained devices and large volumes of distributed data.

3.1 Dynamic Shuffling (DS) Model

The DS model ensures that user data is split into packets and rearranged using a shuffling algorithm dependent on a secret key. The process includes:

1. Converting files into byte streams
2. Splitting into n fragments
3. Applying shuffling based on a chosen permutation cipher
4. Uploading the shuffled packets to cloud storage

This design increases confusion and diffusion, preventing attackers from reconstructing meaningful information without knowing the secret ordering.

3.2 Secret-Shared Dynamic Shuffling (SSDS) Model

To eliminate the single-point dependency on the user-held key, SSDS splits the encryption key between the **Cloud User (CU)** and the **Cloud Service Provider (CSP)** using a **Secret Sharing Scheme (SSS)**.

Key advantages:

- Neither party alone holds the full key
- Compromise of CSP does not reveal the ordering
- A PRF + UUID-based randomization method ensures unique seed values

This dynamic permutation enhances privacy by reducing correlation among data fragments and preventing predictability present in static shuffling.

3.3 Secure Encryption Model (SEM)

SEM introduces

- Secure user authentication,
- Multi-round Hadamard-based transforms,
- Lightweight encryption techniques.

Hadamard transforms are used to rearrange and encode binary data efficiently, replacing traditional heavy cryptographic algorithms. Each encryption round uses a unique prime-based key, and the model ensures:

- high randomness,
- resistance to known-plaintext attacks,
- avalanche effect,
- reduced storage expansion.

4. SECURITY ANALYSIS

4.1 Secure Data Transmission

Splitting data into m fragments drastically reduces the chance of packet interception by attackers. To reconstruct meaningful information, attackers must obtain **all** packets *and* understand the shuffle pattern, which becomes infeasible when m is large. The DS and SSDS models prevent exploitation of browser-based vulnerabilities such as POODLE attacks targeting SSL/TLS.

4.2 Secure Data Storage

Even if packets stored on cloud servers are compromised, attackers cannot reconstruct original data due to:

- unknown permutation ordering
- secret sharing mechanism
- randomization introduced by SSDS

Dynamic shuffling provides significantly lower correlation across neighboring data packets, verified through Euclidean distance measurements.

4.3 Authentication Security

SEM protects credentials from:

- replay attacks
- phishing
- shoulder surfing
- man-in-the-middle attacks

Using Hadamard transforms avoids storing sensitive authentication data in predictable formats.

5. PERFORMANCE EVALUATION

5.1 Execution Time

Tests comparing ECC and the SEM model show:

- approximately **25% reduction** in encryption time for SEM,
- linear scaling with respect to file size,
- significantly lower computational overhead.

This makes the model viable for low-power IoT and mobile devices.

5.2 Storage Requirements

Encrypted data using SEM requires **~10% less storage** than ECC-encrypted files. For large-scale cloud environments, this translates into substantial cost savings for both users and service providers.

5.3 Avalanche Effect

Even a single bit change in plaintext or ciphertext produces large changes in encrypted output (>35%), achieving strong cryptographic randomness.

5.4 Time Complexity Analysis

- ECC complexity: $O(nk + 1)$
- SEM complexity: $O(kn)$

The SEM model provides lower asymptotic time complexity due to elimination of expensive elliptic curve operations.

6. DISCUSSION

The integration of DS, SSDS, and SEM provides a unified framework that:

- enhances availability by reducing encryption bottlenecks,
- improves privacy through multi-layered obfuscation,
- strengthens resilience against cryptographic attacks,
- improves storage efficiency,
- supports real-time cloud operations.

The lightweight nature of these methods makes them suitable for edge devices and large cloud ecosystems.

7. CONCLUSION

This research introduces a comprehensive data protection framework combining dynamic shuffling, secret-shared key management, and multi-round Hadamard-based encryption. The model achieves the dual goals of maximizing data availability and preserving privacy—key requirements in modern distributed computing and cloud storage environments. Performance and security evaluations demonstrate significant advantages over traditional cryptographic models, highlighting this approach as an effective next-generation cloud security solution.

REFERENCES

- [1] Abadi, D. J., Carney, D., Cetintemel, U., Cherniack, M., Conway, C., Lee, S., Stonebraker, M., Tatbul, N., & Zdonik, S. B. (2013). *Aurora: A new model and architecture for data stream management*. VLDB Journal, 12(2), 120–139.
- [2] Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer.
- [3] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
- [4] Hassabis, D., Kumaran, D., Summerfield, C., & Botvinick, M. (2017). Neuroscience-inspired artificial intelligence. *Neuron*, 95(2), 245–258.
- [5] Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255–260.
- [6] Prof. A. Mohamed Azharudheen, Mrs. A. Kumudham, & Ms. S. Kalaivani. “A Scalable Deep Learning-Optimized Data Security Architecture for High-Availability Big Data Environments.” *International Journal of Engineering Research & Technology (IJERT)*, ISSN 2278-0181, Vol. 14, Issue 12, December 9, 2025. DOI: 10.17577/IJERTV14IS120127.
- [7] McCarthy, J., Minsky, M., Rochester, N., & Shannon, C. (1955). *A proposal for the Dartmouth Summer Research Project on Artificial Intelligence*. Dartmouth College.
- [8] Mohamed Azharudheen, A., & Vijayalakshmi, V. (2024). Analyze the new data protection mechanism to maximize data availability without compromising data privacy. *Educational Administration: Theory and Practice*, 30(5), 3911–3922. <https://doi.org/10.53555/kuey.v30i5.3548>
- [9] Russell, S. J., & Norvig, P. (2020). *Artificial intelligence: A modern approach* (4th ed.). Pearson.
- [10] Silver, D., Schrittwieser, J., Simonyan, K., et al. (2017). Mastering the game of Go without human knowledge. *Nature*, 550(7676), 354–359.
- [11] Vaswani, A., Shazeer, N., Parmar, N., et al. (2017). Attention is all you need. In *Proceedings of the 31st Conference on Neural Information Processing Systems (NeurIPS)* (pp. 5998–6008).
- [12] Zhang, Z., & Zhao, R. (2020). Artificial intelligence in modern applications: A survey of theory and practice. *IEEE Access*, 8, 123456–123489.