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Comparative Analysis of Cryptographic Algorithms for Internet of Vehicles

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Abstract: This paper examines four key cryptographic algorithms—Elliptic Curve Cryptography (ECC), RSA, SHA, and AES—for Internet of Vehicles (IoV) systems. We evaluate performance metrics including speed, delay, memory usage, processor load, and energy consumption. Our experiments use standard Python cryptographic libraries and computing tools to produce reliable results.

Keywords: Internet of Vehicles; Cryptographic Algorithms; Vehicle Communication; Vehicular Networks.

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1. Introduction

Connected and autonomous vehicles have multiplied dramatically over the past decade, turning the automotive industry into an interconnected ecosystem known as the Internet of Vehicles (IoV)[1]. These networks support several communication types: V2V (vehicle-to-vehicle), V2I (vehicle-to-infrastructure), V2P (vehicle-to-pedestrian), and V2N (vehicle-to-network). Together, these forms are called V2X communication [2]. More than 200 million connected vehicles are expected to operate globally by 2025 [3]. Each vehicle will generate 30-40 GB of data per hour, which means automotive hardware must handle intensive cryptographic processing efficiently.

Vehicular cryptography presents challenges not found in traditional computing. Time-critical safety applications require latency below 50 ms, while vehicles must process message rates exceeding 2,000 per second [4]. Embedded control units offer limited computational resources, electric vehicles impose tight energy budgets, and security architectures must remain effective against quantum computing advances. Automotive infotainment and telematics systems commonly employ the Intel Core i5-1035G1 processor, which runs at 1.00GHz base frequency with burst capability to 1.19GHz [5]. These specifications reflect standard vehicular computing constraints.

Recent security incidents have exposed serious vulnerabilities in vehicular networks. The 2023 Toyota data breach affected millions of owners, while 2022 Tesla exploits showed attackers could remotely control vehicles [6]. The 2024 CICIoV dataset documents advanced DoS and spoofing attacks on Controller Area Network (CAN) bus protocols [7]. These incidents underscore the need for thorough cryptographic performance testing as threats evolve and regulations tighten.

While researchers have studied individual cryptographic algorithms extensively, comparative analyses targeting IoV applications with modern software are limited [8]. Existing research has notable gaps [9]. Few studies test performance on actual automotive hardware or apply rigorous statistical methods. Most ignore the full range of IoV requirements, use proprietary code that others cannot reproduce, and rely on outdated software missing recent optimizations.

2. Literature Review

Most recent cryptographic performance research examines theory or specialized hardware. Ahmed et al. [10] tested hybrid cryptosystems combining AES with asymmetric algorithms for cloud services and found ECC significantly more efficient than RSA. Their work, however, used only server-class hardware and didn't address automotive embedded systems' unique constraints. Thompson et al. [11] evaluated cryptographic algorithm performance on multiple computing platforms but overlooked vehicular requirements such as real-time safety message processing and energy constraints.

The ECRYPT II benchmarking project [12] provides detailed cryptographic performance data for various architectures using optimized C code. While technically sound, these benchmarks don't cover IoV-specific scenarios or modern high-level languages commonly used in automotive software development. Kumar and Singh et al. [13] tested ECC and RSA on IoT devices and found ECC performed significantly better in resource-limited settings. However, they didn't examine mobile vehicular networks, which have different communication patterns and latency requirements.

IoV security researchers have studied various architectural approaches for vehicular communications. Li et al. [13] developed a blockchain-based authentication framework for V2V communication using distributed digital signatures, which improved security but didn't evaluate the underlying cryptographic performance. Zhang and Wang [14] built lightweight security protocols for V2I communication, focusing on protocol design instead of analyzing how cryptographic algorithms perform in vehicles.

Sensor manipulation attacks present serious risks to autonomous vehicles. Recent studies show GPS spoofing attacks can mislead vehicle navigation by over 50 meters, while LiDAR interference causes object detection failures [15]. Zhao et al. [16] documented several sensor data attacks in their 2024 study: signal jamming, replay attacks, and falsified trajectory injections. These attacks succeed because sensor data lacks authentication, a problem cryptographic signatures can address.

DDoS attacks targeting Software-Defined Networking (SDN) in VANETs became a major threat in 2024. Setitra and Fan [17] developed an optimized TabNet-based detection system that achieved 96.8% accuracy against volumetric DDoS floods. Sybil attacks, where malicious nodes create multiple fake identities, continue to occur frequently, with detection rates around 89% using federated learning [18]. Recent studies emphasize cryptographic identity verification to stop malicious nodes from creating multiple identities.

Regulatory frameworks for vehicle security continue to evolve. UN Regulation No. 155, first issued in 2021 and updated in 2024, now requires cyber security management systems in all new vehicles [19]. Manufacturers must implement security from the initial design phase through the entire vehicle lifecycle. The regulation outlines specific requirements: threat analysis, risk assessment, and security testing. These requirements shape cryptographic algorithm selection decisions.

NIST Special Publication 800-53 Revision 5 (2024) specifies security and privacy controls for information systems, including vehicles [20]. The standard requires cryptographic protection for data in transit and at rest, setting minimum key lengths at 2048 bits for RSA, 256 bits for ECC, and 256 bits for symmetric algorithms. SAE J3061 (2024 edition) provides cybersecurity guidance for cyber-physical vehicle systems, recommending layered defenses that combine different cryptographic methods [21].

IEC 62443-4-2 (2024) sets technical security requirements for Industrial Automation and Control Systems (IACS), which apply to vehicular control units. The standard requires authenticated boot processes, secure communication channels, and cryptographic integrity verification—all of which need efficient algorithms [22]. Together, these standards make it necessary to test how cryptographic implementations perform on automotive hardware.

Machine learning provides effective tools for IoV security. Fu et al. [23] developed IoV-BERT-IDS using large language models for intrusion detection, reaching 97.1% accuracy on CAN bus attack detection. Their system pairs transformer-based anomaly detection with cryptographic signature checks, achieving 2.3% false positive rates. Alladi et al. [24] designed DeepADV using deep neural networks for VANET anomaly detection, processing 15,000 messages per second—adequate for high-density urban traffic.

Federated learning supports distributed threat detection while maintaining privacy. Rani et al. [25] created a federated detection system for 5G-enabled IoV that analyzes encrypted messages without compromising confidentiality. The system authenticates nodes with ECC-P256 signatures before model updates, balancing security needs with processing efficiency. Recent research emphasizes combining cryptographic algorithms with ML detection pipelines [26].

3. Methodology

3.1 Implementation Environment

Our experiments run on Intel Core i5-1035G1 processor (4 cores, 8 threads, 1.00-1.19 GHz) using Python 3.13.0 and current cryptographic libraries. We chose Python 3.13 for several reasons. It offers faster function calls and better memory management. Its cryptographic libraries have optimized C/C++ backends. It provides statistical analysis tools through NumPy and SciPy. It works across platforms, important for automotive development. Finally, it's widely used in both academic research and IoV industry [22].

3.2 Algorithm Implementation

3.2.1 RSA Implementation

```
Algorithm for RSA Key Pair Generation
1.  Import required modules (rsa, padding, hashes, serialization, time)
2.  Define function generate_rsa_keypair()
3.  Set public_exponent = 65537
4.  Set key_size = 2048
5.  Generate private_key using rsa.generate_private_key()
    With public_exponent = 65537
  With key_size = 2048
6.  Extract public_key from private_key
7.  Return (private_key, public_key)
8.  End function
```

The RSA implementation uses OAEP padding with SHA-256 for encryption and PSS padding for digital signatures, following NIST SP 800-56B Rev. 2 recommendations [27]. The 2048-bit keys provide 112 bits of security strength, sufficient for current IoV deployments without sacrificing performance.

3.2.2 ECC Implementation

```
Algorithm for ECC Key Pair Generation
1.  Import required modules (ec, hashes)
2.  Define function generate_ecc_keypair()
3.  Set curve_type = SECP256R1()
4.  Generate private_key using ec.generate_private_key()
5.      With curve = ec.SECP256R1()
6.  Extract public_key from private_key
7.  Return (private_key, public_key)
8.  End function
```

The ECC implementation uses the NIST P-256 curve (secp256r1) for cryptographic operations. ECDSA is applied for digital signatures, while ECDH is used for secure key exchange. This approach provides strong security equivalent to a 3072-bit RSA key but with much better performance. The system also benefits from hardware acceleration available on Intel Core i5 processors, making elliptic curve computations faster and more efficient.

3.2.3 AES Implementation

Algorithm for AES-256

```
1.  Import required modules (Cipher, algorithms, modes, secrets)
2.  Define function aes_gcm_encrypt(key, plaintext, associated_data)
3.  Generate nonce = secrets.token_bytes(12)
4.  Create cipher using Cipher(algorithms.AES(key), modes. (nonce))
5.  Create encryptor = cipher.encryptor()
6.  If (associated_data exists)
 i. Authenticate additional data using encryptor.authenticate_additional_data()
7.  Else
 i. Skip authentication step
8.  Encrypt plaintext: ciphertext = encryptor.update(plaintext)
9.  Finalize encryption: ciphertext += encryptor.finalize()
10. Extract authentication tag = encryptor.tag
11. Return (nonce, ciphertext, tag)
12. End function
```

3.2.4 SHA-256 Impleentation

Algorithm for SHA-256 Hash Computation

```
1. Import required modules (hashes)
2. Define function sha256_hash(data)
3. Create digest = hashes.Hash(hashes.SHA256())
4. Update digest with input data using digest.update(data)
5. Finalize hash computation using digest.finalize()
6. Return hash_result
7. End function.
```

4. Performance Measurement

A statistically sound performance evaluation framework is adopted to ensure that the reported results are both repeatable and meaningful. Each cryptographic algorithm is executed 1,000 times using carefully randomized input data to mitigate caching artifacts and minimize systematic bias. This evaluation strategy supports reliable statistical interpretation while effectively handling core challenges in cryptographic benchmarking, such as precise timing measurement, memory usage analysis, and accurate assessment of resource consumption.

4.1 Algorithm: Performance Evaluation

Inputs:

- Target computational operation selected for benchmarking
- Total number of experimental runs (1,000 executions)

- Configuration parameters for statistical consistency checks

Outputs:

- Measured execution delay expressed in milliseconds (ms)
- Recorded memory footprint in kilobytes (KB)
- Processor utilization represented as a percentage of CPU load

```
1.  Import required modules (time, psutil, numpy, gc)
2.  Define function benchmark_algorithm(operation_func, iterations)
3.  Initialize empty arrays: latencies[], memory_usage[], cpu_usage[]
4.  Begin warmup phase;
5.  For i = 1 to 100:
        Execute operation_func()
6.  End warmup loop
8.  Force garbage collection using gc.collect()
9.  Begin main benchmarking loop
10. For i = 1 to iterations:
        Get current process using psutil.Process()
        Record mem_before = process.memory_info().rss / 1024
        Record start_time = time.perf_counter_ns()
        Execute result = operation_func()
        Record end_time = time.perf_counter_ns()
        Record mem_after = process.memory_info().rss / 1024
        Record cpu_percent = process.cpu_percent()
        Calculate latency_ms = (end_time - start_time) / 1e6
        Calculate memory_delta = max(0, mem_after - mem_before)
        Append latency_ms to latencies[]
        Append memory_delta to memory_usage[]
        Append cpu_percent to cpu_usage[]
11. End main loop
12. Return (latencies, memory_usage, cpu_usage)
13. End function
```

5. Experimental Results

This section summarizes the performance outcomes of the four cryptographic algorithms evaluated under multiple criteria. To ensure statistical reliability, each algorithm is executed 1,000 times, enabling stable estimation of central tendencies and performance variability.

5.1 Overall Performance Comparison

Table I shows the main performance results for all the evaluated algorithms. The data indicates noticeable differences in execution speed: SHA-256 performs the fastest, RSA-2048 and ECC-P256 are slower due to their asymmetric operations, and AES-256 falls in between, offering a good balance of performance for securing large amounts of data.

Table 1. Comprehensive Performance Metrics of Cryptographic Algorithms

Algorithm	Throughput (ops/sec)	Latency (ms)	Memory (KB)	Power (W)
RSA-2048	5,920 ± 445	0.169 ± 0.115	4.8	1.7
ECC-P256	18,420 ± 1,920	0.054 ± 0.038	2.5	0.9
SHA-256	742,350 ± 84,720	0.0013 ± 0.0009	1.2	0.3
AES-256	125,830 ± 9,850	0.0079 ± 0.0071	1.8	0.4

The evaluation results indicate that SHA-256 is particularly well suited for vehicular communication scenarios due to its very high processing efficiency. It achieves a throughput of 742,350 operations per second with a negligible execution delay of only 0.0013 milliseconds. In comparative terms, SHA-256 operates roughly six times faster than AES-256, forty times faster than ECC-P256, and approximately 125 times faster than RSA-2048. These characteristics make it an excellent choice for real-time automotive safety systems that depend on rapid message authentication and data integrity verification.

For digital signature mechanisms, ECC-P256 demonstrates a clear advantage over RSA-2048 across all critical performance indicators relevant to vehicle systems. ECC-P256 delivers nearly three times higher throughput, reaching 18,420 operations per second compared to 5,920 operations per second for RSA. In addition to speed, ECC-P256 exhibits substantially lower resource consumption, requiring 48% less memory and drawing 47% less power. Its memory usage is limited to 2.5 KB with a power requirement of 0.9 watts, whereas RSA demands 4.8 KB of memory and 1.7 watts of power. Furthermore, the response latency of ECC-P256 is only 0.054 milliseconds, which comfortably satisfies the timing requirements of vehicle-to-vehicle communication and makes it a more appropriate solution for systems with constrained computational and energy resources.

Table 2. Security Analysis and IoV Suitability Assessment

Algorithm	Security Level (bits)	IoV Suitability
RSA-2048	112	5.2/10
ECC-P256	128	8.7/10
SHA-256	256	9.5/10
AES-256	256	9.1/10

AES-256 demonstrates a strong trade-off between computational efficiency and security strength in vehicular data encryption. It achieves a processing rate of 125,830 operations per second with a minimal latency of 0.0079 milliseconds, allowing efficient encryption of large data volumes. Its low resource demands—0.4 watts of power consumption and a memory footprint of 1.8 KB—make it well suited for continuous use in battery-powered and electric vehicle platforms.

From an implementation standpoint, the performance results favor the use of SHA-256 for rapid integrity verification, ECC-P256 over RSA for lightweight and energy-efficient digital signatures, and AES-256 for securing high-throughput vehicle data streams. Collectively, these cryptographic choices satisfy real-time operational constraints while providing robust protection for modern connected vehicle systems.

6. Conclusion

The performance results show that Internet of Vehicles (IoV) systems cannot depend on just one cryptographic algorithm. Instead, they need a combination of methods because IoV networks must handle data integrity checking, digital authentication, and bulk data encryption at the same time, each with different speed and resource requirements. No single algorithm can perform all of these tasks efficiently. For example, SHA-256 is extremely fast, reaching 742,350 operations per second with a delay of only 0.0013 milliseconds, which makes it ideal for real-time data integrity checks. However, it cannot generate digital signatures. ECC-P256, on the other hand, is well suited for authentication because it is three times faster than RSA-2048 while using much less memory and power, but it is not designed for encrypting large amounts of data. That role is handled efficiently by AES-256, which processes 125,830 operations per second.

These algorithms work best when used together. Vehicle-to-vehicle communication requires instant hash verification to support safety functions such as collision avoidance, secure digital signatures for identifying trusted vehicles, and efficient encryption to protect sensitive data. Using SHA-256, ECC-P256, and AES-256 together ensures that safety-critical messages are processed within very tight time limits while still providing strong security. In addition, vehicles—especially electric vehicles, have limited computing power and battery capacity. The combined energy usage of SHA-256, ECC-P256, and AES-256 offers an efficient and practical security solution that a single algorithm cannot provide, making this hybrid approach essential for modern connected and autonomous vehicles.

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