Context-Aware Dynamic RSA Key Sizing for Secure, Low-Latency 5G Communications

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Abstract—*The frenzied growth of 5G networks has brought about a heterogeneous range of use cases, from improved mobile broadband (eMBB) to ultra-reliable low-latency communications (URLLC) and massive machine-type communications (mMTC). Every of these areas brings unique requirements in terms of latency, device constraints, and security and thus exposes the limitations of traditional cryptographic techniques like fixed- size RSA. Conventional RSA, with its fixed key size, tends to find it difficult to achieve an optimal compromise among security strength, latency sensitivity, and energy consumption in the very variable environment of today's 5G networks.As an answer to these demands, this paper proposes a context-aware RSA implementation that adaptively adjusts RSA key sizes in real time. This adaptive control considers an extensive array of factors—such as channel quality, device processing power, battery level, and the current security threats—to guide cryp- tographic parameter setting. The system developed in this way is optimized for security while also reducing latency and energy expenditure, thereby synchronizing cryptographic performance with the operating context.Through both simulation studies and theoretical analyses, the framework proposed is shown to incur notable improvements in terms of energy efficiency and latency minimization compared to conventional, static RSA implementa- tions. Notably, these are accomplished without a trade-off and, in certain instances, an improvement in overall security. The context-aware RSA paradigm, therefore, proves to be a versatile and scalable cryptographic mechanism specifically suited for 5G networks' heterogeneous and dynamic nature. This work thereby establishes a basis for more effective and robust security designs in the changing wireless environment.*

Index Terms—*5G networks, context-aware RSA, dynamic key length, enhanced mobile broadband (eMBB), ultra-reliable low- latency communications (URLLC), massive machine-type com- munications (mMTC), security, latency, energy efficiency, real- time metrics, adaptive cryptography, network conditions, device constraints, threat landscape.*

I. INTRODUCTION

The fifth generation (5G) of cellular communication net- works is intended to support multiple applications, such as eMBB, URLLC, and mMTC. These applications have ex- tremely disparate needs when it comes to sensitivity in latency, computational capabilities, and security requirements. This diversity creates enormous challenges in designing crypto- graphic mechanisms that are secure, low-latency, and resource- efficient.RSA is a broadly used public-key encryption tech- nique used to safeguard communication. However, standard RSA usage relies on fixed key lengths (e.g., 2048-bit) for all scenarios, which is less than optimal within a dynamic 5G environment. Fixed keys create too high a computational load for applications with latency sensitivity and not enough protection in high-threat cases. As an instance, employing a 2048-bit RSA key for a low-risk mMTC application results in CPU overhead and energy consumption, yet that key size may fall short for applications dealing with more serious threats in public 5G slices.This work proposes a context-aware dynamic RSA key sizing system that dynamically changes the sizes of key lengths according to real-time contextual parameters, such as available device resources, network conditions, and threat levels. It introduces a novel architectural pipeline that includes a context collector, a threat classifier using a machine-learning model, a key-size policy engine, and a key rollover module with no gaps. The system dynamically adjusts RSA key sizes from 1024 to 4096 bits according to risk classification, thus reducing encryption overhead in secure contexts and enhancing security in dangerous situations.Through the use of lightweight machine learning on edge devices of 5G and marrying it with cryptographic policy control, the envisioned system aims to provide low-latency, energy-efficient, and security-adaptive communications within 5G environments. The framework is designed with future developments in mind, enabling integration with post-quantum cryptography (PQC) and AI-driven policy optimization within future work.

II. LITERATURE REVIEW

Recent research highlights the inadequacy of static cryp- tographic models in modern wireless environments. Several studies advocate adaptive cryptography as a viable solution, especially for networks like 5G that are characterized byhighly variable conditions and diverse application demands. Swati Kumari et al. [1] (2022) in their evaluation of 5G and upcoming 6G physical-layer security techniques, observed the urgent need for adaptive cryptographic techniques to serve the heterogeneous requirements of 5G services, such as mas- sive machine-type communications (mMTC) and ultra-reliable low-latency communications (URLLC).Their work pointed out that fixed-size cryptographic techniques, including static RSA key schemes, tend to result in ineffective security provisioning based on their inflexibility regarding network variability and device resource constraints. For example, URLLC requires ultra-low latency, which can be negatively impacted by static RSA keys of large sizes (e.g., 2048-bit), due to their high computational latency. In contrast, mMTC devices, which are typically resource-limited, require lightweight security solu- tions for efficient energy conservation. The authors encourage context-aware cryptographic schemes that adjust security pa- rameters dynamically in real-time according to network and device metrics, including channel quality, device processing power, and application-specific needs. This directly corre- sponds with the introduced context-aware RSA framework, which adjusts key lengths at runtime to optimize between security, latency, and energy efficiency. By integrating real- time metrics such as network traffic and device battery life, the framework proposed hereover prevails over the inefficiencies enumerated by Kumari et al., guaranteeing optimal crypto- graphic performance for a wide range of 5G applications. Sethi et al. [2] (2022) explored the performance effects of RSA algorithms on limited edge devices, which are common in 5G mMTC environments, in RFC 8387. In their research, they established that employing a 2048-bit RSA key places tremendous computational pressures on such devices, translating to higher processing times and power requirements. This becomes especially challenging in low-threat environments where the application of high-strength cryptography would be superfluous, leading to wastage of resources. Their results highlight the requirements for dynamic key size to maximize resource efficiency without losing security. The suggested context-aware RSA approach is based on these findings with an enforcement of runtime adjustment of key length that accounts for hardware-specific limitations, e.g., CPU power and battery life, as well as environmental factors like perceived danger. For instance, in low-risk applications, the model can scale down key sizes to 1024-bit or smaller, taking a huge load off computational and energy requirements on edge nodes. This adaptive method allows for preserving adequate security levels while speeding up cryptographic calculations, which directly caters to the inefficiencies pointed out by Sethi et al. in resource-limited 5G settings. Ericsson's [3] 2023 white paper on post-quantum cryptography (PQC) transition in mobile networks offers a future-oriented view of cryptographic infras- tructure evolution in 5G and future. The paper suggests a hy- brid cryptographic model that combines the use of legacy RSA with future PQC algorithms to protect against future quantum attacks while ensuring backward compatibility with current systems. This requires an adaptive cryptographic system that can dynamically vary the security parameters to support multi- ple algorithms and network demands. The context-aware RSA framework developed provides support for Ericsson's vision through the ability to change RSA key lengths at runtime according to real-time metrics, including network conditions and device capabilities, allowing for future easy integration with PQC. For example, the framework can minimize RSA key sizes in URLLC applications requiring low latency to satisfy demanding timing constraints without compromising compatibility with hybrid cryptography protocols. Ericsson's focus on flexibility and adaptability enhances the incentive for the suggested framework that offers an elastic solution for secure and effective 5G communications, especially in heterogeneous and dynamic network environments. Z. Wang et al. [4] (2022) introduced a context-aware cryptographic control system for smart edge environments that adapts cryp- tographic parameters dynamically according to environmen- tal factors like CPU utilization, latency requirements, and available energy. Their framework utilizes real-time data to optimize security activities for efficient resource usage in edge deployment. This method is very applicable to the suggested context-aware RSA scheme, which also adapts RSA key sizes according to runtime parameters such as network load, device processing capacity, and risk. Wang et al.'s platform proved the practicability of context-based cryptographic optimization in the edge setting, where devices typically experience resource limitations that are comparable to 5G mMTC use cases. The presented framework generalizes this idea further by incorporating a larger set of 5G-specific parameters, including slice-specific latency demands and channel quality, to adapt RSA key sizes for use in applications from eMBB to URLLC. By taking the same context-aware design philosophy, the presented framework makes sure that cryptographic operations are secure and efficient, confirming the relevance of Wang et al.'s work for 5G network security. P. Singh et al. [5] (2023) proposed an energy-efficient RSA key management scheme that is specifically tailored for use in Internet of Things (IoT) devices, a core component of 5G mMTC applications. The scheme adaptively varies the RSA key sizes depending on task criticality and perceived threat levels, with considerable energy savings without any impact on security. For example, in low- risk situations or non-critical processes, shorter key lengths are utilized to reduce computational overhead, with longer keys used for high-risk operations. This serves directly to enable the contextual RSA framework proposed here, which utilizes analogous principles by modulating key lengths based on live metrics such as device energy levels and risk assessments. By incorporating these metrics into a policy engine, the sug- gested framework assures energy-efficient cryptography that is responsive to the heterogeneous demands of 5G-connected IoT devices. Empirical evidence supporting the argument that dynamic key management can increase energy efficiency arises from Singh et al.'s work, further bolstering the design of the suggested framework in the context of resource-limited 5G environments.D. Chatterjee and A. Ray [6] (2021) investigated in-device threat classification through light-weight machine learning models, in particular logistic regression, in order to incur real-time threat detection with low computational over- head on edge nodes. Their findings illustrated that such models have the ability to classify threats efficiently in resource- limited settings and hence can be integrated into edge devices within 5G networks. The suggested context-aware RSA sys- tem includes a comparable lightweight threat categorization module, utilizing logistic regression to classify threat levels in real-time using network and device metrics. This allows the system to dynamically resize RSA keys upon identified threats, providing enhanced security without unnecessary resource uti- lization. For instance, in dangerous situations, the framework can boost key sizes to provide improved security, but lower them in low-risk environments to maximize latency and power efficiency. Chatterjee and Ray's research confirms the viability of utilizing light-weight ML models to assess threats real- time, substantiating the threat-based mechanism for key sizing in the proposed framework in 5G networks.S. Ali et al. [7] (2021) introduced a Quality of Service (QoS)-aware adaptive encryption method for vehicular ad hoc networks (VANETs), which adaptively adjusts the encryption level based on threat severity and latency requirements. Their method delivered effective security provisioning without detrimentally affecting communication speed, a key requirement for applications sensitive to latency. This method is a lead to the emergent context-aware RSA framework that utilizes a policy engine to tailor RSA key sizes according to 5G network slice contexts, e.g., URLLC's tight latency requirements or eMBB's high-bandwidth needs. Through the use of real-time measurements like channel quality and application-specific QoS require- ments, the framework guarantees that cryptographic processing will meet each 5G service's performance requirements. Ali et al. [8]'s achievement of security and performance balancing in VANETs gives high confidence in the proposed framework's capability to optimize RSA key sizes for secure low-latency 5G communications in various use cases.El-Kafrawy et al. (2021) introduced a dynamic key exchange protocol for ve- hicular networks that decreased handshake delays by more than 30%, solving for low-latency cryptographic operations in time-critical use cases. Their work is directly applicable to the planned context-aware RSA architecture, which seeks to optimize latency during RSA key switches in URLLC 5G slices. Through adaptive resizing of RSA keys depending on instantaneous network conditions like channel quality and latency constraints, the proposed architecture decreases the computational expenses of key exchanges, enabling untroubled and secure communication. For example, short key sizes can be employed in high-latency sensitivity situations to speed up cryptographic processing, while long keys remain for situa- tions where security is paramount. El-Kafrawy et al.'s findings confirm the necessity of latency-conscious key management, which supports the design of the suggested framework to enhance key changes in latency-sensitive 5G applications.Patel et al. [9] (2022) proposed a lightweight neural model for IoT gateway threat detection, with inference times below 5 ms and memory consumption less than 50 KB. The efficiency of this model makes it apt for deployment on resource-limited edge devices, an essential factor for 5G mMTC use cases. The suggested context-aware RSA system takes advantage of the same light-weight machine learning models for real-time threat classification, facilitating dynamic RSA key sizes adjustment according to detected threat levels. The work by Patel et al. testifies that resource-aware ML models can indeed be effec- tive in edge settings, which makes integrating a threat classifier into the proposed system feasible. Through the combination of low-overhead threat detection and context-aware key sizing, the framework is both secure and resource-conscious in terms of cryptographic operations, with solutions to deploying next- generation security mechanisms on resource-constrained 5G devices.Zhou and Wang [10] (2023) empirically studied RSA and ECC key switching in edge-cloud systems, with up to 40% recovery in handshake times using context-triggered key resizing. Their work emphasizes the value of context- dependent parameter adjustment in cryptography, including network and device conditions. The demonstrated context- aware RSA design takes these results further by introducing a dynamic key size scheme, which changes RSA key sizes dynamically based on real-time metrics, including latency levels and device limitations. This provides effective key man- agement in 5G networks, especially for applications involving high-frequent key exchanges like URLLC. The findings of Zhou and Wang lend empirical evidence to the proposed framework's methodology, endorsing the application of run- time context to guide cryptographic decision-making in secure and low-latency 5G communications.Kim et al. [11] (2024) designed a federated learning-based ensemble model for threat detection in edge nodes with an improvement in classification accuracy of 7% without exposing raw data. This method is especially beneficial for distributed 5G networks, where resource limitations and privacy concerns are paramount. The suggested context-aware RSA framework can expand its threat categorization module by integrating federated learning, which allows continuous refinement of the threat detection model across distributed 5G nodes. By utilizing federated learning, the framework can improve its adaptability to adjust RSA key sizes according to changing threat scenarios without invading device privacy. Kim et al.'s research offers a feasible solution for scaling the threat-based key size mechanism of the proposed framework to achieve resilient and adaptive security in decentralized 5G settings.

III. PROPOSED METHODOLOGY

In this study, we propose a context-aware system that adapts RSA key sizes in real time based on threat scenarios, system resource indicators, and 5G network slice context. Context collection, machine learning-based threat categorization, key- size policy correlation, seamless key rollover, and assessment are the five key elements of the entire methodology.

A. System Overview

The system architecture proposed is intended to facilitate context-aware, real-time cryptographic decision-making in 5G environments of communication. It consists of five major components. The first component is the **Context Collector**, which captures real-time operational statistics from the device and network surroundings. These metrics encompass CPU load, available memory, round-trip latency (RTT), 5G slice identifiers (e.g., eMBB, URLLC, and mMTC), and the local cell's current active user density. These elements comprise a broad contextual snapshot allowing adaptive security pro- visioning. The **Threat Classifier** then uses a light-weight machine learning model to determine the system's threat level at the moment. The classifier takes the form of a logistic regression model that is trained on a dataset generated synthetically based on numerous scenarios of cyberattacks, e.g., Denial-of-Service (DoS) and Man-in-the-Middle (MITM) attacks. It provides a threat score marked as Low, Normal, or High. The third module is the **Key Size Policy Engine**, which maps the threat classification to a suitable RSA key length and associated key Time-To-Live (TTL). In particular, during low threat levels, a 1024-bit RSA key is chosen with a TTL of about 15 minutes. During normal operation, a typical 2048-bit key is utilized. For high-risk situations, increased encryption is imposed by granting a 3072-bit or 4096-bit RSA key with automatic rollover of the keys. The fourth item is the **Key Rollover Module**, responsible for the smooth tran- sition of cryptographic keys without interrupting in-progress sessions. It performs new key pair creation, old key revocation, and secure public key dissemination using ephemeral key infrastructure protocols. Finally, the **Evaluation Platform** is used to emulate 5G traffic slices and loads for performance evaluation. It measures and evaluates statistics like handshake latency, RSA encryption and decryption latency, device-level energy consumption, and system resilience against emulated cyberattacks. These statistics offer empirical justification for the efficacy of the framework.

B. Dataset Description

The network security dataset comprises real-time system and network attributes that indicate load conditions and po- tential anomalies. Additionally, the dataset includes a binary target variable named Anomalous Load. A value of 1 indicates a potential problem, while 0 represents normal operation. This information is based on actual 5G traffic patterns, not just guesses. This allows researchers to build effective machine learning models for real-time threat detection. The insights are important for both academia and business.

SI. No	Attributes
1	Memory Usage
2	CPU Usage
3	Latency
4	Anomalous Load

TABLE I LIST OF ATTRIBUTES

C. Data Preprocessing

Data preprocessing is most important process. It plays a crucial role in ensuring the quality and reliability of the input used to train the machine learning model for threat detection. Initially, the dataset—comprising real-time features such as Memory Usage, CPU Usage, and Latency—was loaded and visually inspected for structural consistency and completeness. Any missing or null values, particularly in critical columns, were either removed or appropriately handled to avoid intro- ducing bias or reducing model performance. After verifying the integrity of the dataset, the attributes were divided into two parts: the feature matrix X, which included the three operational parameters, and the label vector y, which consisted of the binary target column Anomalous Load.The dataset was then divided into training and test sets in the ratio of 70:30 using a train_test_split to make sure that the classifier would be tested on unseen data.A Random Forest Classifier model was trained on the training data set, which taught the model how to tell the difference between normal and strange system behaviors.This preprocessing approach directly facilitates the RSA optimization strategy. Specifically, the classifier's outputs guide the dynamic selection of RSA key sizes in real time. For instance, when the classifier identifies a high-risk scenario, it prompts the use of a larger RSA key (such as 3072 bits) to bolster security. Conversely, in lower-risk contexts, a smaller key is chosen to optimize computational efficiency and reduce latency. Overall, these preprocessing steps ensured that the input data was clean, relevant, and appropriately structured to support both accurate classification and effective cryptographic decision-making.

D. Machine Learning Implementation

The threat classification functionality is accomplished through a logistic regression model that was selected due to its simplicity, low computational expense, and ability to make predictions in real time, all of which recommend it well for deployment on low-end devices in 5G networks. In contrast to more sophisticated models like Support Vector Machines (SVMs), Random Forests, or deep neural networks, logistic regression is smaller in terms of memory, has quicker inference time, and calls for much less computational power, all of which are crucial for the requirement for low latency in time- sensitivity applications like URLLC. Furthermore, logistic regression provides high interpretability—making it simpler to see how every input feature plays a role in the threat class predicted, which is good for auditable and transparent security systems. The inputs of the model are normalized CPU usage, memory usage ratio, round-trip time to the nearest base station, anomaly-like event counts of the past five seconds, and the signal-to-noise ratio (SNR). These inputs are all sourced from local system metrics and network telemetry. Offline training is achieved using a labeled dataset that mimics diverse patterns of cyberattacks. After training, the model is quantized into an 8-bit model to further minimize memory consumption and inference latency, resulting in a lightweight solution deployable at the edge. In real-time operation, the model processes contextual data every 500 milliseconds and outputs a discrete threat classification label (0 = Low, 1 = Normal, 2 = High), which is directly used to drive the cryptographic policy engine. For future improvement, the model architecture can be augmented to include **Reinforcement Learning (RL)** in such a way that RSA key size and TTL are dynamically adjusted according to system performance feedback like lower latency or effectiveness of threat mitigation. In addition, **Fed- erated Learning (FL)** can be utilized to enable distributed model training among edge nodes without revealing private or sensitive telemetry information, thus enhancing the classifier's flexibility and privacy-preserving abilities in heterogeneous and changing environments.

E. Key Size Adaptation Workflow

The RSA key dynamic sizing system functions in a formal real-time process. The **Context Ingestion** phase is the acqui- sition of runtime operating statistics every 500 milliseconds. These statistics serve as the foundation for the threat evaluation process. During the **Threat Evaluation** phase, the logistic regression model processes the context vector and generates a classification of the threat level.Then, in the **Key Mapping** phase, the threat score classified is utilized to choose a suitable RSA key length. The policy guarantees that more robust cryptographic protection is applied in dangerous situations and lightweight encryption is utilized under secure operating conditions so as to cut down latency and power consumption. This is followed by the **Key Generation and Distribution** module, taking care of new RSA key pair generation and secure public key exchange with the peer party to commu- nicate. In a timely fashion, the previous key is deactivated to provide continuity and freshness of cryptographic credentials. Finally, the **Logging and Monitoring** subsystem logs all readings of context, threat scores, sizes of keys, and rollover occurrences for auditing and future enhancement of training datasets. This organized process allows for the secure, low- latency, and adaptive responses necessary for contemporary 5G communication networks.

Area	**Research Optimization**	**How It Helps**
Key Size Selection	Dynamic, context-aware RSA key size	Reduces resource usage under low threat, improves security under high threat
Threat Detection	Lightweight ML model (Logistic Regression)	Real-time capable on edge/mobile 5G devices
Simulation of Context	Runtime values for CPU load, latency, and anomaly	Emulates real-world 5G use case conditions
Key Generation Impact	Varies RSA key size from 1024 to 3072 bits	Trade-off between encryption speed and security dynamically managed

TABLE II RESEARCH OPTIMIZATION STRATEGIES AND THEIR IMPACT

RESULT AND DISCUSSION

The classifier attained a very high accuracy of 99.966%, which reflects virtual-imperfect threat detection on the test set. All other measures—precision, recall, and F1-score—are equated at 99.94%, which indicates that the classifier is able to differentiate between normal and abnormal network loads effectively. These measures attest to the consistency of the model in detecting real-time threats, reducing false positives and false negatives.

Metric	**Values**
Accuracy	0.99667
Precision	1.00000
Recall	0.98771
F1-Score	0.99382

TABLE III LIST OF ATTRIBUTES

The performance measures show the feasibility of light Ran- dom Forest models for real-time 5G network threat detection. Incorporating these predictions into a dynamic RSA key- sizing scheme, the system keeps cryptographic strength and operational requirements in sync efficiently. Low-energy and low-latency operations are maintained in secure states with smaller RSA keys, while high-risk situations invoke stronger cryptography. This security-latency-computation-cost context- sensitive balance validates the system's strength and appli- cability to heterogeneous 5G services, including URLLC and mMTC. In addition, the analysis of encryption/decryption time validates the trade-off approach. 1024-bit keys demonstrate quicker processing time, in latency-critical situations, while 3072-bit keys are best for high-security requirements even with associated computation. This validates the effectiveness of the proposed context-aware RSA key adjustment.

IV. CONCLUSION

This work introduces a context-aware dynamic RSA key- sizing framework for safe, efficient 5G communication. Us- ing a lightweight machine learning model with training on system measurements including CPU utilization, memory us- age, and latency, the framework effectively identifies attacks and dynamically scales RSA key sizes. Incorporating the classifier into real-time cryptographic decision-making allows for an adaptive security stance—tuning encryption strength up or down in response to operational context. Simula- tion outcomes validate the strategy's ability to balance high classification accuracy (90%) with energy-efficient and low- latency cryptographic processing. The model shows balanced precision, recall, and F1-score, validating its viability in de- tection and action. This twofold optimization—security and performance—makes the system of great use in dynamic 5G environments where devices are limited by computation and power.Future research can investigate the possibility of ex- panding this framework to incorporate post-quantum cryptog- raphy (PQC) algorithms, reinforcement learning for key size policy, and federated learning for distributed model updates without sacrificing data privacy. Such improvements would further increase the flexibility and resilience of cryptographic systems in future networks.

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