Department of Computer Science

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Survey of Privacy Enhancing Technologies in the Energy Sector

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ABSTRACT

The energy sector is undergoing significant transformations, driven by the integration of renewable energy sources and digital technologies such as smart grids, dynamic energy pricing, and smart metering. While these advancements enhance operational efficiency and grid management, they also introduce significant privacy concerns due to the extensive data collection associated with these technologies. Privacy Enhancing Technologies (PETs) are crucial in safeguarding sensitive information while enabling the continued use of data for operational improvements.

This dissertation explores the applicability and effectiveness of PETs in the energy domain, with a particular focus on their role in protecting consumer privacy within smart grid environments that are increasingly vulnerable to cyber-attacks and data leakage. The research employs a comprehensive methodology, including a systematic literature review and a comparative analysis of key PETs, such as homomorphic encryption, differential privacy, secure multi-party computation (SMPC), and trusted execution environments (TEEs).

The study examines specific use cases, including secure billing, decentralized energy trading, and data aggregation in smart metering systems. Findings indicate that no single PET can fully meet all privacy protection requirements, as trade-offs between privacy, data utility, and implementation complexity are inherent in these technologies. Additionally, the effectiveness of PETs varies significantly depending on data types, operational environments, and regulatory frameworks.

The dissertation concludes with actionable recommendations for stakeholders in the energy sector, emphasizing the need to raise awareness of PETs, update regulatory frameworks, and encourage future research focused on developing more efficient and scalable privacy-enhancing techniques. As the energy sector continues its digital transformation, robust privacy protection will be essential for balancing the benefits of data-driven innovation with the imperative of consumer privacy protection.

1. INTRODUCTION

1.1 Background

The energy sector is undergoing a transformative shift, driven by the integration of smart grids, IoT devices, and distributed renewable energy sources. These innovations have significantly improved operational efficiency, enabling real-time monitoring, load balancing, and decentralized energy trading. At the core of this digital transformation are smart meters and IoT-enabled devices, which continuously collect vast amounts of energy consumption data. This data provides critical insights for energy providers to optimize grid performance, implement dynamic pricing, and forecast energy demand.

However, the collection and processing of such granular data raise serious privacy concerns. Smart meters, for instance, can reveal sensitive details about household occupancy patterns, appliance usage, and even personal habits. These concerns are exacerbated by the increasing risk of cyber-attacks, data breaches, and unauthorized data access in energy systems.

In response to these challenges, Privacy Enhancing Technologies (PETs) have been developed to protect sensitive data while allowing energy providers to maintain operational efficiency. PETs such as Homomorphic Encryption (HE), Secure Multi-Party Computation (SMPC), Blockchain with Privacy Enhancements, and Trusted Execution Environments (TEEs) play a pivotal role in ensuring data privacy and security in smart grid environments. These technologies enable secure data processing, transmission, and aggregation without exposing sensitive information to unauthorized entities.

1.2 Problem Statement

Despite the potential of Privacy Enhancing Technologies (PETs) to safeguard consumer privacy in the energy sector, there are several challenges hindering their widespread adoption and implementation. These challenges include:

- Scalability Issues: PETs like Homomorphic Encryption and SMPC introduce significant computational and communication overhead,

making them difficult to scale for large-scale, real-time energy systems such as national grids.

- Energy Consumption: Blockchain, particularly when used with consensus mechanisms such as Proof of Work (PoW), consumes a large amount of energy, which is incompatible with the energy-saving goals of smart grids.
- Interoperability: Integrating PETs into existing energy infrastructure often requires substantial modifications, making it difficult for energy providers to adopt these technologies without incurring high costs.
- Regulatory Compliance: Privacy-preserving technologies must comply with regulatory frameworks such as GDPR, which can be challenging for decentralized systems like blockchain that struggle to meet the "right to be forgotten" requirement.

These issues hinder the effective use of PETs in protecting consumer data while maintaining the efficiency of energy systems. The need for scalable, energy-efficient, and compliant privacy-preserving technologies in smart grid environments remains largely unmet.

1.3 Research Objective

The objective of this research is to conduct a comparative analysis of key Privacy Enhancing Technologies (PETs) and privacy-preserving schemes used in smart grids, with the goal of:

1. **Evaluate Privacy-Preserving Schemes:** To evaluate the effectiveness of different privacy-preserving schemes (e.g., Paillier Encryption, SMPC, Blockchain with zk-SNARKs) in ensuring data privacy and security in smart grid systems.
2. **Assess Authentication Mechanisms:** To assess the strength and applicability of authentication mechanisms (e.g., Digital Signatures, Blockchain Consensus Protocols) in smart grids, particularly in verifying the authenticity of devices and ensuring secure communication.
3. **Analyze Scalability and Energy Efficiency:** To analyze the scalability and energy efficiency of the selected schemes and determine their practicality for large-scale, real-time smart grid applications.

4. **Investigate Implementation and Integration Challenges:** To investigate the challenges in implementing and integrating these schemes into existing smart grid infrastructures, focusing on cost of implementation, interoperability, and regulatory compliance.
5. **Compare Compliance with Regulatory Standards:** To compare the ability of these schemes to comply with existing privacy regulations such as GDPR and identify schemes that best align with regulatory requirements for data protection.

2. LITERATURE REVIEW

2.1. Introduction

The digitalization of the energy sector, driven by the proliferation of smart grids and Internet of Things (IoT) devices, has introduced significant privacy challenges. These challenges stem from the extensive collection, processing, and sharing of detailed energy consumption data, which may expose personal behaviors, such as household occupancy patterns and usage trends, to potential misuse or unauthorized access.[21] [22] To mitigate these risks, a variety of Privacy Enhancing Technologies (PETs) have been developed.

Key PETs include:

1. **Homomorphic Encryption (HE) for data aggregation**

Homomorphic encryption (HE) is a cryptographic technique that allows computations to be performed directly on encrypted data without needing to decrypt it first. This property is critical in scenarios where privacy must be maintained throughout the data lifecycle, from collection to processing and analysis [22] [14] [26].

2. **Secure Multi-Party Computation (SMPC) for energy data analysis**

Secure Multi-Party Computation (SMPC) is a cryptographic method that allows multiple parties to compute a function over their combined inputs while keeping each party's input private. SMPC is particularly useful in scenarios where stakeholders—such as energy providers.[13] [18]

3. **Blockchain Technology with zk-SNARKs for Peer-to-Peer Energy Trading**

Blockchain is a decentralized, distributed ledger technology that ensures the immutability and transparency of data transactions. In blockchain, every transaction is recorded in a block, and each block is linked to the previous one, forming a secure chain of data. The decentralized nature of blockchain means that there is no central authority, and the ledger is maintained by a network of nodes.[14] [22]

4. **Trusted Execution Environments (TEEs) for Confidentiality and Integrity.**

Trusted Execution Environments (TEEs) provide a hardware-based approach to secure data processing. TEEs create a secure, isolated environment within a device where sensitive data can be processed, even if the rest of the system is compromised. A popular implementation of TEEs is Intel SGX, which creates an enclave for secure computations.[17]

A TEE operates as an isolated execution environment that runs parallel to the main operating system. Within the TEE, data can be processed securely, ensuring that even if the device is compromised by malware or unauthorized access, the data inside the TEE remains protected. TEEs rely on secure hardware to ensure that only trusted code can execute within the enclave.[17]

2.2. Privacy Preservation in Smart grid

2.6 Paillier Encryption for Data Aggregation

Paillier Encryption is a widely recognized homomorphic encryption scheme that allows computations on encrypted data without needing to decrypt it. This property is essential in privacy-preserving data aggregation, particularly in smart grids, where the energy consumption data from households is sensitive and must remain confidential throughout computations. Paillier's additive homomorphic property makes it ideal for scenarios like total energy consumption aggregation without revealing individual household consumption values [21] [22].

The Paillier encryption scheme consists of three main steps: Key Generation, Encryption, and Decryption. Below are the mathematical formulations for each step:

1. **Key Generation**
   - **Selection of Large Prime**
     - Choose two large prime numbers, *p* and *q*
     - The product of these primes *N* is computed as:

$$\boldsymbol{N = p \times q}$$

The security of Paillier encryption relies on the difficulty of factoring ***N***, a product of two large primes, which forms part of the public key.

   - **Modulus Computation:**
     - The modulus NNN is used in all encryption and decryption operations. In the Paillier scheme, all operations are performed modulo N^2 which provides a large

$$\boldsymbol{N^2 = (p \times q)^2}$$

   - **Calculation of λ(lambda):**
     - Compute λ, the least common multiple (LCM) of p−1 and q−1:

$$\boldsymbol{\lambda = lcm\,(p-1, q-1)}$$

     - λ is part of the private key and is used during the decryption process.

   - **Selection of Generator *g:***
     - Choose $g \in \mathbb{Z}^*_{\{N^2\}}$ where $\mathbb{Z}^*_{\{N^2\}}$ denotes the multiplicative group of integers modulo N^2. The generator *g* must satisfy certain properties to ensure the homomorphic property.

   - **Public and Private Key:**
     - The public Key is ***(N, g),*** while the private key is $\boldsymbol{\lambda}$

2. Encryption

To encrypt a plaintext message $\boldsymbol{m} \in \mathbb{Z}_N$ representing a household's energy consumption data, the following steps are performed:

- **Random Number Selection:**
  - Choose a random $\boldsymbol{r} \in \mathbb{Z}_N^*$ number where ***r*** is coprime to ***N*.** The random number ***r*** ensures that the encryption of the same message mmm results in different ciphertexts, providing semantic security.
- **Ciphertext Computation:**
  - The ciphertext ***C*** is computed using the following formula:

$$\boldsymbol{C = g^m * r^N mod\ N^2}$$

  - Here, $\boldsymbol{g^m}$ ensures that the plaintext mmm is encrypted, while $\boldsymbol{r^N}$ introduces randomness into the ciphertext to prevent attackers from recognizing patterns in the encrypted data.

3. Decryption

The decryption process is used to retrieve the plaintext message mmm from the ciphertext ***C*** using the private key ***λ***.

- **Decryption Process**:
  - The plaintext ***m*** is recovered using the following formula:

$$\boldsymbol{m = \frac{L(C^{\lambda} mod\ N^2)}{L(g^{\lambda} mod\ N^2)} mod\ N}$$

  - The function ***L(x)*** is defined as:

$$\boldsymbol{L(x) = \frac{x-1}{N}}$$

This function ensures the extraction of the plaintext from the ciphertext by performing modular arithmetic with respect to ***N***.

- **Mathematical Breakdown:**
  - $\boldsymbol{C^{\lambda} mod\ N^2}$ computes the ciphertext raised to the power of the private key **λ** which reduces the ciphertext in such a way that allows the plaintext to be extracted.

- $L(g^{\lambda} mod\ N^2)$ensures that the result is valid and normalizes the computation to recover the correct plaintext.

4. Homomorphic Property of Paillier Encryption

One of the most important features of Paillier encryption is its additive homomorphic property, which allows encrypted values to be added together without needing to decrypt them first. This is crucial in smart grids where the total energy consumption of multiple households needs to be aggregated without accessing individual consumption data.

Mathematical Expression of the Homomorphic Property:

Let's assume two households report their encrypted energy consumption data as C_1 and $C_2$where:

$$C_1 = g^{m1} * r^N mod\ N^2$$

$$C_2 = g^{m2} * r^N mod\ N^2$$

- Here, $m1\ and\ m2$are the plaintext energy consumption values of the two households.
- To compute the encrypted sum of these values:

$$C_{sum} = g^{m1+m2} * (r1 * r2)^N mod\ N^2$$

Thus, the result is an encryption of the sum of the plaintext values **m1+m2** without needing to decrypt the individual values first.[21] [22]

- **Application Example in smart grid**

For instance, if two households report encrypted energy consumption data, C_1 and C_2 the grid operator can compute the total consumption:

$$C_{total} = C_1 * C_2$$

The result, C_{total} represents the encryption of the total consumption of both households. The grid operator can compute the total energy consumption without accessing the individual consumption data.

2.2.2 Secure Multiparty Computation

Secure Multi-Party Computation (SMPC) allows multiple parties to compute a joint function over their inputs while ensuring the privacy of those inputs. In smart grids, SMPC is crucial for collaborative energy data analytics, where multiple entities such as energy providers or grid operators need to compute aggregate functions (e.g., total consumption) without revealing individual consumption data.[21] [22]

Mathematical Overview

Two widely used SMPC protocols in the context of privacy-preserving energy data analysis are Yao's Garbled Circuits and the Goldreich-Micali-Wigderson (GMW) protocol. These protocols are based on secure computation over shared data.

I. Yao's Garbled Circuits

Yao's Garbled Circuits protocol allows one party (the garbler) to transform a Boolean circuit representing the computation into an encrypted or garbled form, while the second party (the evaluator) evaluates the garbled circuit without learning the input values.

Mathematical Steps:

1. **Key Generation (Garbling the Circuit):**
   - For each wire in the circuit (e.g., a binary input X_1 or X_2), The garbler assigns two random keys:

$$\boldsymbol{W^0_{x1}}, \boldsymbol{W^1_{x1}} \quad \text{and} \quad \boldsymbol{W^0_{x2}}, \boldsymbol{W^1_{x2}}$$

   These values represent the garbled input for 0 and 1.

2. **Gate Computation (Garbling Logic Gates):**
   - For each gate in the circuit (e.g., AND, OR), the garbler encrypts the output wires using the garbled values from the input wires. If the gate is an AND gate, for example, the garbled gate is computed as follows:

$$\boldsymbol{Garbled\ AND}\ (\boldsymbol{W^i_{x1}}, \boldsymbol{W^j_{x2}}) = \boldsymbol{Enc}(\boldsymbol{W^{i\wedge j}_{output}})$$

Where i, j ∈ {0,1}. This encryption ensures that the evaluator can compute the output of the gate without learning the inputs.

3. **Evaluation:**
   The evaluator receives garbled inputs W_{x1}, W_{x2} and evaluates the garbled circuit by performing the corresponding garbled operations:

$$Evaluate(w_{x1}, w_{x2}) = Garbled\ AND(w_{x1}, w_{x2})$$

   The evaluator uses the garbled values to perform the computation without accessing the plaintext values.
4. **Output Decryption:**

Once the garbled circuit has been evaluated, the evaluator decrypts the final garbled output to retrieve the result of the computation, which could represent the total energy consumption or any other aggregate result in a smart grid.

II. Goldreich-Micali-Wigderson (GMW) Protocol

The GMW protocol works by securely distributing shares of the inputs across the parties, ensuring that no single party knows the complete input. Computations are performed using Boolean circuits over these shares.

Mathematical Steps:

1. **Input Sharing:**
   - Let x_A be the input of Party A (e.g., energy consumption of Provider A), and x_B be the input of Party B (e.g., energy consumption of Provider B).
   - Each party splits their input into shares such that the sum of the shares reconstructs the original input. For instance:

$$\boldsymbol{x_A = x^1_A \oplus x^2_A}\ ,\quad \boldsymbol{x_B = x^1_B \oplus x^2_B}$$

where $\boldsymbol{x^1_A}$ and $\boldsymbol{x^1_B}$ are sent to the other party.

2. **Secure Computation (XOR and AND Gates):**
   - The parties then perform operations on the shares using Boolean logic gates:
   - **XOR Gate:**

$$z = x_A \oplus x_B$$

The XOR operation is performed separately on the shares from each party:

$$z^1 = x^1_A \oplus x^1_B \,,\; z^2 = x^2_A \oplus x^2_B$$

- **AND Gate:**

$$z = x_A \wedge x_B$$

The AND operation is computed over the shares using distributed multiplication techniques, which ensure that no party learns the full input:

$$z^1 = x^1_A \wedge x^1_B, \quad z^2 = x^1_A \wedge x^1_B$$

3. **Result Reconstruction:**
   - After the computation, the parties combine the results of their shares to reconstruct the final output: $z = z^1 \oplus z^2$
   - This provides the result (e.g., total energy consumption or aggregated pricing) without revealing the original inputs of either party.

Application in Smart Grids

In smart grids, SMPC is essential for collaborative tasks like energy data aggregation, demand forecasting, and energy pricing:

- **Total Energy Consumption**: Let x_A and x_B represent the energy consumption of two energy providers. Using GMW, they can compute:

$$z = x_A + x_B$$

without revealing their respective energy consumption.

- **Pricing Calculation:** If providers need to calculate the average energy price based on private consumption data, they can securely compute the aggregate price using Yao's Garbled Circuits or GMW, preserving the privacy of their data.

2.2.3 Blockchain with zk-SNARKs for Peer-to-Peer Energy Trading

Blockchain technology, when enhanced with zk-SNARKs (Zero-Knowledge Succinct Non-Interactive Arguments of Knowledge), offers a powerful solution for maintaining privacy in decentralized energy trading. In smart grids, blockchain is used to enable peer-to-peer energy trading, allowing prosumers (producers and consumers) to trade energy directly without relying on a central authority. The use of zk-SNARKs ensures that transactions are private while still verifiable on the blockchain, maintaining transparency and integrity. The zk-SNARK protocol involves three key steps: Key Generation, Proof Generation, and Verification. These steps ensure that a prover can convince a verifier that a transaction is valid without revealing any details about the transaction itself.

1. Key Generation (Trusted Setup Phase)

The first step in a zk-SNARK system is the key generation, which is performed during a trusted setup phase. This setup creates the public and private parameters needed for subsequent operations:

- **Public Parameters $\boldsymbol{pp}$:**
  - The trusted setup generates public parameters $\boldsymbol{pp}$, which are used by the prover to generate proofs and by the verifier to check the validity of the proofs.
  - Public parameters consist of structured reference strings (SRS) that include random values and cryptographic commitments.
- Private Parameters $\boldsymbol{sk}$:
  - Private parameters $\boldsymbol{sk}$ are used during the proof generation process but remain confidential and are not shared.

Mathematically, the key generation function can be described as:

$$(\boldsymbol{pp}, \boldsymbol{sk}) = \boldsymbol{Setup}(\mathbf{1}^{\boldsymbol{\lambda}})$$

Where $\boldsymbol{\lambda}$ is the security parameter that defines the bit length of the keys. The output consists of the public parameters $\boldsymbol{pp}$ and the secret key $\boldsymbol{sk}$.

2. Proof Generation

In the proof generation phase, the prover generates a cryptographic proof $\boldsymbol{P}$ that asserts the correctness of a computation (e.g., verifying that a transaction is valid) without revealing the transaction details. The

prover computes the proof using the private parameters $\boldsymbol{sk}$ and the public parameters $\boldsymbol{pp}$

- Prover's Task:
  - The prover holds the secret transaction data x (e.g., amount of energy traded, sender and receiver addresses) and generates a proof P showing that the transaction is valid according to a function $f(x)$, without revealing x.
  - The function $f(x)$, could represent the transaction validity rule, such as verifying that the transaction amount does not exceed the balance of the sender's account.

Mathematically:

$$\boldsymbol{P = Prove(pp, sk, x)}$$

Where PPP is the cryptographic proof generated by the prover, xxx is the secret input (e.g., transaction data), and pp and sk are the public and private parameters, respectively.

3. Verification

Once the prover generates the proof $\boldsymbol{P}$, the verifier checks the validity of the proof using the public parameters $\boldsymbol{p}$. The verifier does not learn any details about the transaction itself, only that the proof verifies the correctness of the transaction.

- Verifier's Task:
  - The verifier runs a function to check the proof:

$$\boldsymbol{Accept/Reject = Verify(pp, P)}$$

- If the proof is valid, the verifier accepts the transaction; otherwise, it rejects the transaction.

In this process, the verifier can be confident that the transaction follows the rules (e.g., the transfer of energy is valid and the sender has sufficient balance) without needing to know the transaction details.

Application in Smart Grids

In smart grids, blockchain with zk-SNARKs is particularly useful for enabling peer-to-peer energy trading while ensuring that transactions remain private and secure. Prosumers can trade energy directly on the blockchain without relying on intermediaries, while zk-SNARKs provide

privacy by hiding sensitive transaction details (such as the amount of energy traded or the identities of the prosumers) from the public ledger.

Example of zk-SNARKs in Smart Grids:

1. **Peer-to-Peer Energy Trading:**

- Prosumers (both producers and consumers of energy) can trade energy in a decentralized manner using blockchain. Each transaction involves a proof PPP that confirms the transaction's validity without exposing the energy amount or the parties involved.

2. **Blockchain Transparency and Privacy:**

- zk-SNARKs ensure that the blockchain remains transparent (all transactions can be verified), while individual transactions remain private. This balance between transparency and privacy is critical in smart grids, where both trust and confidentiality are necessary.

2.5 TEEs for Secure Data Processing in Smart Grid

Trusted Execution Environments (TEEs) provide hardware-based security by creating isolated environments (enclaves) within devices. These enclaves are designed to protect sensitive computations and data from unauthorized access, even if the device's operating system or applications are compromised. Intel SGX is a prominent TEE solution used in smart meters and IoT devices in smart grids to secure energy consumption data and ensure confidentiality and integrity during data processing.[13]

Technical Overview of TEEs:

TEEs isolate sensitive computations within secure enclaves, ensuring that only trusted code can access or modify the data. This is critical in smart grids, where millions of smart meters and IoT devices collect and process real-time energy consumption data, which must remain secure and confidential throughout its lifecycle.

- **Enclave Creation**
- TEEs create secure enclaves that operate independently of the device's operating system. These enclaves can only be accessed by authorized code running within the enclave.

- Intel SGX creates such enclaves, ensuring that data processed within them cannot be read or tampered with by unauthorized entities, including the operating system or hypervisor.
- Enclave Memory Isolation: The enclave's memory is encrypted and separated from the main system's memory, preventing external processes from accessing the enclave's data.

Data Processing Within Enclaves

- TEEs process sensitive data within the secure enclave, ensuring that even if the system is compromised, the data remains protected.
- For instance, smart meters in smart grids process real-time energy consumption data, but the data remains confidential as long as it is handled within the enclave.

Remote Attestation

- Remote attestation allows external parties (e.g., grid operators) to verify that the data processed within the enclave remains secure and that the enclave has not been tampered with.
- The enclave generates a cryptographic report that can be verified using public-private key cryptography. This ensures that the computations have been performed securely within the enclave.

Application of TEEs in Smart Grids

TEEs, such as Intel SGX, are particularly effective in securing IoT devices and smart meters in smart grids. They provide a secure environment for processing sensitive energy consumption data, ensuring that personal data is not exposed to external threats.

Example in Smart Grids:

- Smart Meter Security: TEEs can be embedded in smart meters to protect the real-time energy data that is collected and transmitted to grid operators. The smart meter can process this data securely in the enclave and provide a summary or encrypted output, ensuring that personal energy usage data remains confidential throughout the process.
- Secure IoT Device Processing: TEEs enable IoT devices in smart grids to handle sensitive tasks securely, such as controlling

distributed energy resources (DERs) or aggregating data from different sources while maintaining privacy and integrity [13].

2.3 Authentication Mechanism in Smart Grid

2.3.1Digital Signatures

Digital Signatures, particularly the **Elliptic Curve Digital Signature Algorithm (ECDSA),** are widely used in smart grids to ensure the authenticity and integrity of messages exchanged between devices. In the context of smart grids, ECDSA ensures that only authenticated devices (such as smart meters and IoT devices) can communicate with the grid, preventing unauthorized data access or manipulation.[13] [22]

Technical Overview of ECDSA

The Elliptic Curve Digital Signature Algorithm (ECDSA) is a variant of the Digital Signature Algorithm (DSA) that operates on elliptic curve cryptography. ECDSA offers high security with smaller key sizes, making it particularly efficient and well-suited for resource-constrained environments like IoT devices in smart grids.

1. Key Generation
   - ECDSA begins with the generation of a public-private key pair. The private key is used to sign messages, and the public key is used by others to verify that the signature was created by the legitimate holder of the private key.
   - Elliptic Curve Operations:
     - Choose an elliptic curve E defined over a finite field $\mathbf{F}_p$where ppp is a prime number.
     - Select a point G on the elliptic curve, called the base point.
     - The private key d is a randomly chosen integer, and the corresponding public key is: $\boldsymbol{Q = d \times G}$ where G is the base point and d is the private key. The point multiplication $\boldsymbol{d \times G}$ is a fundamental operation in elliptic curve cryptography.

2. Signing

- To sign a message, the sender uses their private key to generate a digital signature, ensuring that the message can only be validated by those with access to the corresponding public key.

- Signature Generation:
  - The message to be signed is first hashed using a cryptographic hash function $H(m)$.
  - A random integer k is selected, and the signature is calculated as a pair of values (r, s) :

$$\boldsymbol{r = (k \times G)_x \; mod \;\; n}$$

where $(k \times G)_x$ is the x-coordinate of the elliptic curve point, and is the order of the base point.

$$\boldsymbol{s = k^{-1}(H(m) + d \times r) mod \; n}$$

The values (r, s) form the digital signature for the message.

3. Verification

- The verifier uses the public key of the sender to verify the signature. The verifier ensures that the message has not been tampered with and that it was indeed signed by the legitimate entity holding the corresponding private key.
- Signature Verification:
- The verifier computes:

$$\boldsymbol{w = s^{-1} \; mod \; n}$$

$$\boldsymbol{u_1 = H(m) \times w \; mod \; n}$$

$$\boldsymbol{u_2 = r \times w \; mod \; n}$$

- The verifier then checks whether:

$$\boldsymbol{(u_1 \times G + u_2 \times Q)_x \equiv r \; mod \; n}$$

- If the equation holds, the signature is valid, confirming that the message was signed by the holder of the private key corresponding to the public key Q.

Application of Digital Signatures in Smart Grids

Digital Signatures, particularly ECDSA, are widely used in smart grid environments to authenticate devices and ensure that only legitimate entities can exchange data with the grid. This ensures that all data transmitted within the grid comes from trusted devices, preventing unauthorized access, tampering, or data forgery.[13]

Examples in Smart Grids:

- **Smart Meter Authentication:**
    - Each smart meter generates a digital signature when transmitting energy consumption data to the grid operator. The grid operator verifies the signature using the smart meter's public key, ensuring that the data originates from an authorized meter and has not been altered.
    - ECDSA is particularly suited for this scenario due to its efficiency in generating and verifying signatures, even on resource-constrained devices like smart meters and IoT sensors.
- **IoT Device Authentication:**
    - IoT devices in smart grids (such as distributed energy resources or sensors) use ECDSA to sign messages and communicate securely with the grid control systems.
    - The use of digital signatures ensures that only authenticated devices can send control commands or report data, reducing the risk of malicious attacks.

2.4 Challenges of schemes in Smart Grid

- Paillier Encryption, while highly effective for data aggregation due to its homomorphic properties, faces significant challenges in terms of computational complexity. The modular arithmetic required for encryption and decryption is resource-intensive, making it difficult to apply Paillier encryption to large datasets or real-time applications in smart grids. Furthermore, the encryption process introduces latency, which can hinder the performance of time-sensitive tasks like grid balancing and demand response programs. The energy consumption associated with these complex operations is also a concern, especially in environments where efficiency is paramount, such as IoT-based smart grids.[22]
- Secure Multi-Party Computation (SMPC), used in multi-party collaborative systems, addresses the need for privacy in joint computations but suffers from high communication overhead. In SMPC, secure exchanges between multiple parties are required, and as the number of participants grows, so does the communication complexity. This results in scalability issues, making SMPC less suitable for large-scale smart grids. Additionally, the requirement for multiple rounds of secure exchanges introduces latency, which is

problematic in applications requiring real-time data processing. Like Paillier encryption, SMPC also consumes significant energy due to the need for secure exchanges, limiting its applicability in resource-constrained environments like IoT devices.[13] [21]

- For Blockchain with zk-SNARKs, the main challenge lies in its energy consumption and computational complexity. Blockchains that rely on Proof of Work (PoW) for consensus are known to be energy-intensive, which conflicts with the energy-saving goals of smart grids. While zk-SNARKs improve the privacy of blockchain transactions by allowing verification without revealing transaction details, they add to the computational complexity of the system. This, combined with the inherent scalability issues of blockchain, particularly in public blockchains, limits the practicality of blockchain systems in large-scale smart grids. Furthermore, integrating blockchain into existing centralized grid infrastructures is difficult due to its decentralized nature, which often requires significant architectural changes.[22]
- Digital Signatures (ECDSA), while highly effective for authentication and integrity, do not inherently provide privacy. While ECDSA ensures that messages come from legitimate devices and have not been tampered with, the contents of the messages remain exposed unless encryption is applied alongside the signatures. In terms of computational requirements, ECDSA is generally efficient but may still pose challenges for resource-constrained devices like IoT sensors and smart meters in smart grids. Additionally, the management of public-private key pairs in large distributed systems like smart grids can be complex and require significant administrative oversight.[13]
- Finally, Trusted Execution Environments (TEEs), such as Intel SGX, provide hardware-based security by creating secure enclaves for device-level data processing. However, TEEs face significant scalability challenges due to their reliance on specialized hardware, which may not be available across all devices in a large, distributed smart grid. TEEs are particularly effective at protecting data within a single device, but they do not support multi-party computations or complex cross-device data processing. Additionally, hardware dependencies limit the flexibility of TEEs, and deploying TEE-enabled devices across a large smart grid can be costly.[13][19]

In summary, while each of these schemes—Paillier Encryption, SMPC, Blockchain with zk-SNARKs, Digital Signatures, and TEEs—provides strong privacy or authentication guarantees, their computational demands, energy consumption, scalability limitations, and integration challenges must be addressed to make them viable for large-scale smart grid deployments.

2.5 Future Directions

The evolution of smart grids demands ongoing advancements in privacy-preserving technologies and authentication mechanisms to ensure secure and efficient management of energy systems. Several key challenges—such as scalability, energy efficiency, and real-time processing—still need to be addressed. Based on the current state of the literature and the limitations identified in various schemes like Paillier Encryption, SMPC, Blockchain with zk-SNARKs, Digital Signatures, and TEEs, this section outlines future directions for improving privacy and security in smart grids.

1. Enhancing Scalability for Large-Scale Smart Grid Deployments

Problem: Schemes like Paillier Encryption and SMPC struggle with scalability due to their high computational and communication overhead. As smart grids expand, involving millions of IoT devices and smart meters, these schemes face significant performance bottlenecks.

Future Direction: Research should focus on improving the scalability of privacy-preserving schemes by adopting parallel computation techniques and exploring multi-key homomorphic encryption. These approaches can reduce computational overhead by enabling efficient aggregation and secure multi-party computations over large datasets.[11][13]

2. Improving Energy Efficiency in Blockchain-Based Systems

Problem: Blockchain, particularly when combined with Proof of Work (PoW) for consensus, is energy-intensive, making it unsuitable for energy-sensitive environments like smart grids. Even privacy-preserving enhancements like zk-SNARKs add computational complexity, further increasing energy consumption.

Future Direction: Future research should explore alternative consensus algorithms such as Proof of Stake (PoS) and Delegated Proof of Stake (DPoS) to reduce the energy demands of blockchain systems used in smart grids. Integrating PoS-based blockchains with privacy-preserving techniques like zk-SNARKs could provide a more energy-efficient solution for decentralized energy trading [21].

Developing energy-efficient cryptographic techniques, such as those that optimize elliptic curve operations, can reduce energy consumption in both blockchain and digital signature schemes [13].

3. Integrating Privacy-Preserving Schemes with TEEs

Problem: While TEEs provide device-level privacy, they do not inherently support multi-party computations or large-scale, cross-device data processing. Additionally, TEEs are limited by hardware dependencies.

Future Direction: A promising direction is to integrate TEEs with other privacy-preserving schemes like SMPC or Paillier Encryption to enable secure multi-party computations across devices while ensuring device-level data protection. This hybrid approach would allow smart grids to benefit from both privacy-preserving computation and hardware-level security, ensuring that sensitive data remains protected throughout the computation lifecycle [21] [22].

4. Adoption of Privacy-Preserving Federated Learning

Problem: As smart grids become more interconnected, the need for decentralized analytics grows. Traditional centralized data processing poses privacy risks, and current schemes struggle with multi-party data aggregation.

Future Direction: Federated learning is an emerging technology that allows data to be processed locally on devices, with only aggregated results shared with a central server. By combining federated learning with privacy-preserving techniques such as differential privacy or homomorphic encryption, smart grids can perform secure, decentralized analytics without exposing individual household data. This approach could provide a scalable and privacy-conscious solution for managing large datasets across millions of smart meters and IoT devices [11].

2.6 Regulatory Compliance and Legal Implications

As smart grids become more data-driven and interconnected, ensuring compliance with data privacy regulations such as the General Data Protection Regulation (GDPR) is paramount. Privacy-preserving schemes and authentication mechanisms must meet stringent legal requirements to protect consumer data, ensure transparency, and foster trust in energy systems. This section explores the regulatory challenges and the legal implications of adopting privacy-preserving technologies in smart grids.[6][19]

1. **General Data Protection Regulation (GDPR) and Data Privacy**

The GDPR, implemented in the European Union, places strict rules on how personal data is collected, processed, and stored. In the context of smart grids, this includes data collected from smart meters and IoT devices that can reveal sensitive information about household energy consumption patterns.

- Key GDPR Requirements:
  - **Right to be Forgotten:** Consumers have the right to request the deletion of their personal data. Privacy-preserving technologies must ensure that individual energy data can be removed from systems when requested, without compromising the overall functionality of the grid.
  - **Data Minimization:** Data controllers (e.g., energy providers) are required to collect and process only the minimum amount of personal data necessary for the task. Privacy-preserving schemes like Paillier Encryption and SMPC can help achieve this by enabling data aggregation without revealing individual data [21].

2. **Blockchain and Regulatory Compliance Challenges**

While blockchain offers transparency and security for decentralized energy trading, it also presents compliance challenges, particularly with respect to GDPR:

Immutability vs. Right to be Forgotten:

- One of the core features of blockchain is its immutability—once data is added to the blockchain, it cannot be changed or deleted. This conflicts with GDPR's Right to be Forgotten, which requires that personal data be erasable upon request. This legal conflict

poses a significant challenge for blockchain implementations in smart grids [21].

- Future Directions: Researchers are exploring the use of privacy-enhancing technologies like zk-SNARKs and off-chain storage to address this challenge. For instance, sensitive personal data could be stored off-chain, while only cryptographic proofs are stored on the blockchain, allowing for compliance with data deletion requests.

3. Trusted Execution Environments (TEEs) and Compliance

Trusted Execution Environments (TEEs) provide hardware-based security at the device level, which can help ensure compliance with data protection laws by securing data processing in smart meters and IoT devices.

- Data Security and Integrity:

  TEEs, such as Intel SGX, ensure that data processed within the enclave remains confidential and tamper-proof, helping smart grid operators meet GDPR requirements for data security. By keeping data encrypted and isolated during processing, TEEs protect sensitive energy data from unauthorized access, reducing the risk of data breaches.[6] [13]

2.7 Conclusion

The literature has demonstrated that Privacy Enhancing Technologies (PETs) are indispensable for addressing the privacy concerns arising from the increasing digitalization of the energy sector. Each PET provides distinct advantages when applied in contexts, such as smart grid operations, but they also present significant challenges that hinder their widespread adoption.

Technologies like homomorphic encryption and Secure Multi-Party Computation (SMPC) provide strong privacy protection by enabling computations on encrypted data or private inputs without compromising confidentiality. However, these technologies struggle with scalability and impose high computational overhead, particularly in large-scale energy systems, limiting their practicality in real-time applications [25], [16]. Trusted Execution Environments (TEEs) offer secure, hardware-based processing capabilities, ensuring data protection even in compromised environments. However, TEEs are constrained by hardware scalability,

making them difficult to deploy across densely populated smart grid areas [3]. Blockchain technology, particularly when enhanced with zk-SNARKs, presents a decentralized solution for secure energy trading but suffers from high energy consumption and scalability issues, especially when applied in real-time energy applications [25], [24].

The financial implications of implementing PETs, particularly for smaller energy providers, further limit their adoption. The high cost of deploying SMPC, homomorphic encryption, or blockchain can be prohibitive, and the absence of standardized protocols complicates efforts to ensure interoperability across different energy systems. Additionally, the varying regulatory frameworks across regions make it difficult to ensure compliance, further restricting the deployment of these technologies [21].

Moreover, ethical considerations have emerged as a critical concern. Issues such as data transparency, data sovereignty, and informed consent need to be addressed to ensure the responsible deployment of PETs. Achieving a balance between privacy protection and user trust is essential for gaining public support and regulatory approval for the use of these technologies [6].

In conclusion, while PETs are crucial for ensuring privacy and data security in the energy sector, their practical deployment faces numerous challenges, including technical limitations, high energy consumption, financial barriers, and regulatory compliance issues. Future research must focus on improving the scalability of PETs, reducing their energy demands, and establishing global standards for their implementation to facilitate broader adoption and ensure compliance with privacy regulations.

3. METHODOLOGY

3.1 Introduction

This chapter outlines the methodology used to compare various Privacy Enhancing Technologies (PETs) relevant to the energy sector. The comparison is structured around specific criteria identified through an extensive review of existing literature. These criteria are designed to evaluate the effectiveness, scalability, and applicability of PETs in different energy sector contexts, grid operations. The PETs selected for this study have been chosen based on a combination of relevance, prevalence in the literature, and technical applicability to energy systems. The selection process is explained in detail in the next section.

3.2 Selection of Privacy Preserving and Authentication Scheme

Selected Schemes:

- **Paillier Encryption:** A homomorphic encryption scheme used for privacy-preserving data aggregation in smart grids. It allows computations on encrypted data without needing to decrypt it, ensuring that individual user data remains private during aggregation [21].
- **SMPC (Secure Multi-Party Computation):** SMPC is used to enable collaborative computations between multiple parties without revealing their individual data. This makes it useful for multi-party collaboration in smart grids, where privacy must be maintained during joint analysis [11].
- **Blockchain (with zk-SNARKs):** Blockchain, enhanced with zero-knowledge proofs (zk-SNARKs), was selected due to its decentralized nature and ability to secure peer-to-peer energy trading while ensuring transaction privacy [21].
- **Digital Signatures:** Digital signatures are widely used in smart grids to ensure the authenticity of messages and data exchanged between smart meters, grid operators, and IoT devices. Signatures, such as the Elliptic Curve Digital Signature Algorithm (ECDSA), ensure that data is signed by a legitimate entity, preventing unauthorized access or tampering [13].

- **Trusted Execution Environments (TEEs):** TEEs provide hardware-based security for smart grid devices, ensuring that sensitive data is processed in secure enclaves, even if the system is compromised [21].

Schemes Excluded:

Several schemes were excluded from this review due to their limited applicability or technical limitations in smart grid environments. These include:

- **Federated Learning**: Although federated learning is an emerging technology for decentralized data processing, it was excluded because it is still in its early research stages and lacks widespread adoption in smart grids.
- **Zero-Knowledge Proofs (ZKPs)**: While ZKPs provide strong privacy guarantees, they are computationally intensive and are not widely implemented in real-time energy systems.
- **Fully Homomorphic Encryption (FHE): While** FHE supports arbitrary computations on encrypted data, its computational complexity makes it impractical for real-time energy applications, as it introduces significant latency and requires substantial computational resources.

3.3 Development of Comparison Criteria.

To effectively compare these PETs, the following criteria were developed, informed by the review of literature across the selected papers:

1. Privacy Protection Level

Definition: The degree to which the scheme can safeguard sensitive data from unauthorized access, breaches, and potential misuse, ensuring that energy data remains confidential throughout its lifecycle (from collection to processing to storage).

Justification: The energy sector handles sensitive data, such as individual energy consumption patterns, household occupancy information, and operational data from critical infrastructure. As noted in several studies [25], [23], PETs must offer strong privacy guarantees to

prevent unauthorized entities from accessing or misusing this data. For instance, homomorphic encryption ensures that data remains encrypted during computation, preventing any exposure even during processing. SMPC achieves privacy by splitting data among multiple parties so that no single party has full visibility of the data. The robustness of privacy protection provided by each scheme must be evaluated to ensure it meets the sector's stringent privacy needs.

2. Authentication Strength

Definition: The ability of the scheme to perform essential functions, such as data encryption, analysis, and aggregation, without introducing significant delays, latency, or degradation in the overall system performance. This criterion assesses how well the PET operates in time-sensitive environments, such as smart grids, where real-time data processing is critical.

Justification: Authentication is critical in preventing unauthorized devices from accessing the grid. Digital Signatures (e.g., ECDSA) ensure that messages are signed by legitimate devices, preventing spoofing or tampering [13].

3. Energy Consumption

Definition: The amount of energy required to operate the PET, including the computational resources it consumes. Energy consumption is especially relevant in smart grids and energy-sensitive environments, where the overhead introduced by the PET could impact overall grid efficiency.

Justification: Schemes that require substantial computational power often consume large amounts of energy, making them less suitable for resource-constrained environments like smart meters or IoT devices. For example, studies have shown that blockchain, especially in its public or **Proof of Work (PoW)** form, is notoriously energy-intensive [5], [13]. High energy consumption can also be prohibitive for PETs like fully homomorphic encryption, which requires continuous computation over encrypted data [15]. In the energy sector, the cost of operating a PET must be balanced against its privacy benefits. A PET that consumes too much energy may undermine the very goal of efficient energy

management and might not be feasible for smaller providers with limited resources.

4. Scalability

Definition: The ability of the scheme to maintain its effectiveness and performance as the deployment scale increases, from small residential setups to large-scale grid operations that cover millions of consumers and multiple energy providers.

Justification: Energy systems must be able to scale efficiently. This is especially challenging for schemes like SMPC and blockchain. SMPC's performance deteriorates as the number of participants increases due to the need for secure multiparty communication [1], [3]. Similarly, blockchain faces significant challenges when scaling to large networks, as every participant must process and store each transaction, leading to storage and computational bottlenecks [4]. In the energy sector, where large-scale data aggregation and real-time decision-making are crucial, PETs need to be able to handle increasing data loads and more complex infrastructures without compromising privacy or performance.

5. Interoperability

Definition: The ease with which the schemes can integrate with existing systems, technologies, and infrastructures in the energy sector, including smart meters, IoT devices, data aggregators, and grid management systems.

Justification: Energy systems are heterogeneous, consisting of legacy infrastructure and modern IoT devices that must work together seamlessly. Schemes need to be interoperable across these varied environments. For example, TEEs like Intel SGX are relatively easy to integrate into IoT environments because they work at the hardware level, providing a secure enclave for data processing. However, integrating PETs like SMPC and homomorphic encryption into these systems may require significant modifications to existing software and workflows [6], [8]. Blockchain's interoperability can also be complex due to its decentralized nature and the need for all nodes to adopt the same protocol. Ensuring that a scheme can be deployed without causing

major disruptions to existing systems is crucial for its widespread adoption.

6. Regulatory Compliance

Definition: The extent to which the Schemes aligns with existing legal and regulatory frameworks governing data privacy and security in the energy sector, including global and regional laws like the General Data Protection Regulation (GDPR) in Europe and the California Consumer Privacy Act (CCPA) in the U.S.

Justification: Regulatory compliance is a key concern for energy providers, particularly in regions with stringent data protection laws like Europe. PETs must ensure compliance with laws such as the GDPR, which mandates that personal data be protected and that individuals have control over their data [6], [19]. Differential privacy, for instance, is particularly effective in meeting GDPR requirements, as it allows for aggregate data analysis while protecting individual privacy. On the other hand, blockchain's immutable nature presents challenges for compliance with "right to be forgotten" clauses in privacy regulations [19]. The ability of a scheme to adapt to various regulatory environments is therefore critical to its viability in the energy sector.

7. Cost of Implementation

Definition: The total cost associated with deploying the PET, including the initial investment in infrastructure, ongoing maintenance, and operational costs related to energy consumption, computational power, and human resources.

Justification: Many PETs require significant upfront costs and ongoing expenses, making them less accessible to smaller energy providers. For example, fully homomorphic encryption involves high costs due to its complex algorithms and the computational power needed to perform encrypted operations [6], [9]. Blockchain, especially in decentralized forms, requires significant storage and processing power, translating into higher operational costs. For energy providers with limited resources, cost is a deciding factor when choosing a Scheme. Studies [6], [9] indicate that the high costs associated with some scheme can act

as a major barrier to adoption, particularly for utilities operating in regions with tight financial margins or underdeveloped infrastructure.

8. Ease of Integration

Definition: The complexity involved in incorporating the scheme into existing energy systems, workflows, and infrastructures, including the ease of deployment, configuration, and maintenance.

Justification: Deploying scheme in energy systems must be minimally disruptive to existing processes and infrastructure. TEEs, for example, can be integrated relatively easily into IoT devices without requiring significant changes to software architecture. Differential privacy can also be incorporated into existing data analytics systems with minimal adjustments, as it operates primarily at the algorithmic level [7], [10]. In contrast, SMPC and homomorphic encryption require more complex changes to workflows, as these technologies demand new ways of handling and processing data securely [15]. For energy providers, ease of integration directly impacts the speed and cost of deployment, making it a critical factor for practical adoption.

3.4 Justification of Criteria Developed

The criteria for comparison were chosen to reflect the operational, security, and regulatory challenges faced by smart grids. Each criterion was selected to evaluate how well the privacy-preserving and authentication schemes perform in terms of scalability, privacy protection, and regulatory compliance:

- **System Model:** This is important for determining where each scheme can be applied most effectively. For instance, Blockchain is more suited for decentralized systems, while Paillier Encryption works well in centralized data aggregation [21].
- **Scalability and Energy Consumption**: Smart grids involve millions of IoT devices, so it's crucial to determine how each scheme scales with increasing system size and what its energy demands are [21].
- **Security and Privacy Requirements**: Schemes must meet strict security and privacy standards to protect personal energy data. Schemes like Paillier Encryption and SMPC are focused on

maintaining privacy during data aggregation and collaboration [21, 11].

- **Regulatory Compliance**: GDPR and other data privacy regulations impose strict requirements on the collection, storage, and sharing of personal data. Privacy-preserving schemes must comply with these regulations to be viable in smart grid systems [21].

3.5 Methods for Comparison

The selected Scheme will be evaluated against the established criteria through a comprehensive literature-based analysis. The comparison will be conducted using both qualitative assessments and quantitative metrics, where applicable. This evaluation process will culminate in a matrix table presented in the results chapter, offering a clear, visual comparison of each PET across the selected criteria. The steps for this evaluation are as follows:

1. **Literature-Based Scoring**: Each scheme will be scored based on findings from the literature regarding its performance on the key criteria—privacy protection level, computational overhead, scalability, energy consumption, cost of implementation, regulatory compliance, interoperability, and ease of integration. Scores will be assigned by synthesizing data from peer-reviewed studies, industry reports, and relevant academic papers. These scores will provide a quantitative representation of how each PET performs on each criterion.
2. **Synthesis in Matrix Table:** The results of the literature-based scoring will be organized into a matrix table. This table will be presented in the results chapter and will provide a side-by-side comparison of how each scheme performs against the established criteria.

4. RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents the results and discussion of the comparative analysis of selected Privacy Preserving and Authentication scheme in the energy sector. The comparison is based on smart metering, peer-to-peer energy trading, grid balancing, and data aggregation. Each

scheme—Homomorphic Encryption, SMPC, TEEs, Blockchain is evaluated using key criteria such as privacy protection, scalability, energy consumption, and ease of integration. The findings are summarized in a matrix table, followed by a detailed discussion.

4.2 Comparison of Privacy Preserving and Authentication Schemes.

Criteria	Paillier Encryption	SMPC	Blockchain with zk-SNARKs
Privacy Protection Level	Strong privacy, allowing computations on encrypted data without revealing the plaintext [25], [21].	High privacy by enabling joint computation across parties without revealing individual data [11].	Strong privacy through zk-SNARKs, ensuring transaction privacy while maintaining transparency [21].
Authentication Strength	N/A (focus on privacy	N/A (focus on multi-party privacy)	Moderate—zk-SNARKs offer privacy, but authentication depends on blockchain consensus mechanisms [21].
Energy Consumption	High, due to the complexity of modular arithmetic and homomorphic encryption [21].	High—due to the need for multiple secure exchanges and multi-party communication [11].	Very high—Public blockchains using Proof of Work are energy-intensive; zk-SNARKs add computational overhead [21].
Scalability	Struggles with large	Limited—communicatio	Moderate—zk-SNARKs reduce

	datasets, especially in real-time scenarios due to computational demands [21].	n overhead increases with the number of participants, reducing scalability [11].	verification time, but consensus mechanisms limit scalability [21].
Performance Efficiency	Computationally intensive, leading to high latency in real-time applications [25].	Suffers from high communication delays due to secure multi-party exchanges [11].	Moderate—zk-SNARKs add complexity, though blockchain performance is influenced by consensus mechanisms [21].
Interoperability	Moderate—requires significant adaptation to integrate into legacy systems [21].	Low—difficult to integrate due to multi-party communication complexity [11].	Low—Public blockchains are difficult to integrate into centralized systems due to decentralization [21].
Regulatory Compliance	High—Complies with GDPR and data privacy regulations by ensuring data remains encrypted [25], [21].	Moderate—Complies with privacy regulations, but governance across multi-party settings is complex [11].	Moderate—Blockchain immutability conflicts with GDPR's "right to be forgotten," posing challenges for compliance [21].
Cost of Implementation	High—Expensive due to the computational resources required for encryption [21].	Very high—Communication costs make SMPC expensive to implement, especially for large grids [11].	High—Blockchain infrastructure and zk-SNARKs are computationally expensive and require substantial storage [21].
Ease of	Moderate—	Low—	Low—Blockchain's

Integration	Challenging to integrate due to the complexity of handling encrypted data [21].	Complex multi-party protocols make it difficult to integrate into existing workflows [11].	decentralized nature makes integration into centralized systems difficult [21].

Table 4.2.1 Comparison of Schemes

Criteria	**Digital Signature (ECDSA)**	**TEEs**
Privacy Protection Level	Offers data integrity and authenticity, but lacks built-in privacy for message content [13].	Ensures device-level privacy by securing data within hardware-based enclaves [21].
Authentication Strength	Strong—Ensures device and message authentication using elliptic curve signatures, preventing spoofing [13].	Limited authentication—focuses more on hardware-based data security than identity verification [21].
Energy Consumption	Low—Efficient for resource-constrained environments, making it suitable for IoT systems [13].	Low—Energy-efficient processing in secure enclaves [21].
Scalability	High—Scales well across large distributed systems with minimal computational overhead [13].	Moderate—Scales for small to medium-sized deployments, but constrained by hardware dependencies [21].
Performance Efficiency	High—Fast and efficient signature verification; low latency [13].	High—On-device processing ensures low latency and fast performance [21].

Interoperability	High—Easy integration into existing smart grid systems for authentication [13].	Moderate—Easily integrated into IoT devices but constrained by hardware dependencies [21].
Regulatory Compliance	High—Complies with GDPR and other data security laws, ensuring message authenticity and integrity [13].	High—Meets GDPR and other data privacy regulations due to secure enclave-based processing [21].
Cost of Implementation	Low—Digital signatures are cost-effective, requiring minimal computational power [13].	Moderate—Requires investment in specialized hardware (e.g., Intel SGX) but lowers operational costs due to energy efficiency [21].
Ease of Integration	High—Easily integrated into existing systems for device and message authentication [13].	Moderate—Easy integration into IoT systems but limited by hardware constraints [21].

Table 4.2.2 Comparison of schemes Continued

4.3 Discussion on Results

The results highlight key strengths, limitations, and trade-offs among the privacy-preserving technologies (PETs) and authentication schemes used in smart grids, focusing on privacy protection, authentication strength, energy consumption, scalability, and regulatory compliance.

1. Privacy Protection Level

Each PET provides varying levels of privacy protection, which is essential in smart grids to secure sensitive data from households and IoT devices.

- Paillier Encryption ensures strong privacy through its homomorphic encryption, allowing computations on encrypted

data without revealing the underlying information. However, the computational overhead limits its practical use in large-scale or real-time deployments [25], [21].

- SMPC provides high privacy by enabling joint computations across multiple parties without exposing individual inputs, making it valuable in collaborative energy markets. However, communication overhead limits its scalability in larger, real-time systems [11].
- Blockchain with zk-SNARKs offers strong privacy in decentralized energy trading by enabling private transactions without revealing sensitive details. However, zk-SNARKs add computational complexity, affecting scalability [21].
- Digital Signatures (ECDSA) focus on data integrity and authentication but do not inherently provide message privacy, requiring additional encryption for secure data transmission [13].
- TEEs provide device-level privacy by securing data in hardware enclaves, ensuring that even if a device is compromised, the data inside remains secure. However, TEEs do not support multi-party computations [21].

2. Authentication Strength

Strong authentication is crucial for ensuring that only authorized devices communicate within the grid, preventing unauthorized access and tampering.

- Digital Signatures (ECDSA) offer strong authentication by ensuring that messages are signed by legitimate devices, preventing unauthorized access and ensuring data integrity. This makes them ideal for IoT devices, which have limited computational resources [13].
- Blockchain with zk-SNARKs provides moderate authentication through its consensus mechanisms, but its focus is more on privacy and transaction verification rather than direct device authentication [21].
- Paillier Encryption and SMPC prioritize privacy preservation over authentication, ensuring data confidentiality during computation but not verifying sender or receiver identities.

- TEEs focus on securing data within the device rather than verifying device identity, offering limited authentication [21].

3. Energy Consumption

Energy consumption is a critical factor for the deployment of PETs in resource-constrained environments like smart grids.

- Blockchain has the highest energy consumption, especially with Proof of Work (PoW) for consensus, making it unsuitable for energy-sensitive environments [21]. Even with zk-SNARKs, energy consumption remains a concern.
- Paillier Encryption and SMPC also exhibit high energy demands due to their cryptographic complexity and secure multi-party exchanges, limiting their practical deployment in large-scale energy systems [25], [11].
- Digital Signatures (ECDSA) and TEEs are energy-efficient, making them ideal for use in smart meters and IoT devices, where energy resources are limited [13], [21].

4. Scalability

Scalability is a significant challenge for most PETs and authentication schemes, especially in large-scale smart grids.

- Blockchain with zk-SNARKs faces moderate scalability challenges, with the decentralized nature of blockchain and consensus mechanisms like PoW limiting its efficiency in large networks [21].
- Paillier Encryption and SMPC struggle with scalability due to their computational and communication overhead, making them less suitable for real-time applications and large deployments [25], [11].
- Digital Signatures (ECDSA) scale well, providing efficient computation across large networks with minimal overhead, making them ideal for distributed smart grid systems [13].

- TEEs exhibit moderate scalability but are limited by hardware requirements, making large-scale deployment costly and complex [21].

5. Regulatory Compliance

Regulatory compliance is critical for any smart grid technology, particularly in regions governed by strict data protection laws like GDPR.

- Paillier Encryption and SMPC align well with GDPR by ensuring data remains encrypted or distributed across multiple parties without revealing the entire dataset, making them suitable for environments where personal data must be protected [25], [11].
- Blockchain faces challenges with GDPR due to its immutable nature, which conflicts with the right to be forgotten. Although zk-SNARKs provide privacy, they do not solve the issue of data deletion [21].
- Digital Signatures (ECDSA) comply with data security regulations, ensuring data authenticity and integrity, making them suitable for securing communications in smart grids [13].
- TEEs also comply with GDPR by securing data within hardware enclaves, ensuring that sensitive data is processed securely and remains protected during computation [21].

6. CONCLUSION

This thesis explored the application of Privacy Enhancing Technologies (PETs) and authentication mechanisms in addressing the privacy and security challenges faced by smart grids. As the energy sector continues its transition toward digital infrastructures, the collection and processing of sensitive data such as household energy consumption raise critical privacy concerns. Through the comparison of technologies like Paillier Encryption, Secure Multi-Party Computation (SMPC), Blockchain with zk-SNARKs, Digital Signatures (ECDSA), and Trusted Execution Environments (TEEs), the research provided a detailed analysis of how each PET and authentication scheme performs across key criteria such as privacy protection, authentication strength, energy consumption, scalability, and regulatory compliance.

Paillier Encryption was found to offer strong privacy protection by allowing encrypted computations during data aggregation, making it suitable for centralized smart grid operations. However, its computational complexity results in significant latency and high energy consumption, limiting its practicality for large-scale or real-time grid applications. Similarly, SMPC was identified as highly effective in collaborative energy markets, enabling joint computations without revealing individual data inputs. However, SMPC's scalability is hindered by its communication overhead, which increases as more parties are involved in the computation.

Blockchain with zk-SNARKs provides strong privacy for peer-to-peer energy trading by allowing transactions to be verified without revealing sensitive transaction details. While zk-SNARKs enhance privacy, blockchain's reliance on Proof of Work (PoW) introduces substantial energy consumption, making it less viable for energy-sensitive environments like smart grids. Additionally, while Digital Signatures (ECDSA) were found to provide strong authentication and data integrity, they do not inherently offer privacy, requiring additional encryption measures to secure message content. Despite this, ECDSA’s low energy consumption makes it an ideal solution for IoT devices and smart meters.

Trusted Execution Environments (TEEs), such as Intel SGX, proved to be highly effective at securing sensitive data within hardware-based

enclaves, ensuring that device-level data remains protected even if the broader system is compromised. However, TEEs are limited by their reliance on specialized hardware, which presents scalability challenges in large-scale grid deployments.

In terms of energy consumption, Blockchain with PoW emerged as the most energy-intensive technology, while ECDSA and TEEs were found to be the most energy-efficient options, making them ideal for deployment in IoT-based energy systems. Paillier Encryption and SMPC also consume significant energy due to their cryptographic complexity and communication overhead.

Scalability remains a key issue for several PETs, with Blockchain, Paillier Encryption, and SMPC struggling to scale in large smart grid deployments due to their computational demands. Digital Signatures (ECDSA), on the other hand, scale well across large distributed systems with minimal computational overhead. TEEs, though moderately scalable, are limited by hardware dependencies that restrict their widespread deployment.

From a regulatory compliance standpoint, Paillier Encryption, SMPC, and Digital Signatures align well with regulations like GDPR, which requires that personal data remain encrypted or distributed among multiple parties. Blockchain's immutability, however, conflicts with GDPR’s right to be forgotten, making it more difficult to achieve full compliance. TEEs ensure compliance by securing data within hardware-based enclaves, thus preventing unauthorized access.

In conclusion, while each technology offers strong privacy protection and authentication capabilities, their adoption in smart grids faces challenges related to scalability, energy efficiency, and regulatory compliance. Future research should focus on enhancing the scalability and energy efficiency of these technologies to ensure their practicality for large-scale and real-time energy applications.

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