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Editorial Comments Volume 4 Issue 4

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Volume 4, Issue 4 of the *Journal of Computers, Mechanical and Management (JCMM)* presented a collection of interdisciplinary research contributions that explored the intersection of smart technologies, sustainable systems, and secure infrastructures. The issue featured **four original research articles** and **one mini-review**, addressing applications in smart cities, blockchain-integrated IoT systems, sustainable transportation, secure manufacturing, and nanocomposite materials.

Naresh Thoutam et al. [1] investigated the performance gains offered by edge computing in smart city applications. Their simulation-driven study revealed *an 86.67% latency reduction, 61.11% bandwidth savings, and 58.33% energy efficiency gains*, supporting the case for decentralized processing in urban environments. **Chetan Chauhan et al.** [2] proposed a blockchain-based framework that enhanced secure communication in smart IoT systems. Leveraging symmetric encryption, consensus protocols, and smart contracts, their architecture demonstrated resilience to cyber threats while maintaining communication integrity and low latency. **Munmun Kakkar et al.** [3] offered a mini-review on the role of electric vehicles (EVs) in sustainable transportation. Drawing from global policy trends, life-cycle data, and infrastructure analysis, the review outlined key enablers and challenges in scaling EV adoption, including battery sustainability, grid integration, and equity in access. **Anamika Singh et al.** [4] presented a simulation-based framework for AR-enabled smart manufacturing that integrated machine learning and blockchain. Their study showed improvements in task efficiency (25%), safety (40%), and training duration (35%), demonstrating the feasibility of immersive, secure, and intelligent industrial operations under the Industry 4.0 paradigm. **Manindra Trihotri and U.K. Dwivedi** [5] analyzed the dielectric and electrical behavior of carbon nanotube and carbon black–epoxy nanocomposites. Their experimental results revealed that filler type and frequency significantly influenced activation energy and dielectric constants, offering insights for high-performance material design in electronics and energy storage.

Announcement

We are pleased to announce that the *Journal of Computers, Mechanical and Management* **was** officially assigned the **ISSN (Online): 3009-075X** by the ISSN National Centre for Malaysia on **8 September 2025**. This registration **marked** a milestone in the journal's growth, enhancing its visibility, discoverability, and prospects for indexing. As Editor-in-Chief, I thank the editorial board, authors, reviewers, and publishing partners for their support in upholding the journal's standards. We invite researchers to submit original manuscripts and participate in future special issues as we continue our mission to publish impactful, interdisciplinary research at the intersection of computing, engineering, and management.

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The Role of Edge Computing in Enhancing the Performance of Smart City Applications

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Abstract

The rapid proliferation of smart city initiatives has generated vast amounts of data from heterogeneous sources, including sensors, Internet of Things (IoT) devices, and mobile applications. Traditional cloud infrastructures face high latency, bandwidth constraints, and scalability issues in handling such massive real-time data streams. Edge computing addresses these limitations by decentralizing data processing and bringing computation closer to the data source. This paradigm enables faster response, lower latency, optimized bandwidth use, and improved resilience. For applications such as traffic management, public safety, energy optimization, and environmental monitoring, edge computing significantly enhances efficiency and scalability. This paper investigates the role of edge computing in smart city applications, discusses benefits and challenges, and presents performance models focusing on latency reduction, bandwidth optimization, and energy efficiency. The study highlights how edge computing can be integrated into sustainable smart city frameworks to enhance urban living standards.

Keywords: Edge Computing; Smart Cities; Real-Time Data Processing; Internet of Things (IoT); Decentralized Computing; Urban Infrastructure

1. Introduction

The rapid growth of urban populations and technological advancements has accelerated the deployment of smart city infrastructures. These ecosystems integrate the Internet of Things (IoT), cloud computing, big data analytics, and artificial intelligence to improve the quality of life, optimize resource usage, and enhance safety and sustainability [1–3]. IoT devices deployed across cities generate massive volumes of heterogeneous data from transportation, healthcare, energy, and governance systems, requiring efficient and timely processing. Traditional cloud computing architectures, while offering scalability and centralized management, face challenges of high latency, bandwidth consumption, and limited responsiveness when supporting real-time and mission-critical services [2, 4]. Applications such as connected vehicles, intelligent surveillance, and healthcare monitoring require ultra-low latency and high reliability, which cloud-only models cannot deliver [3, 5]. These limitations have motivated research into fog and edge computing paradigms. Edge computing extends computation and storage closer to end devices, thereby reducing end-to-end latency, optimizing bandwidth, and improving energy efficiency. Surveys and systematic reviews consistently demonstrate that edge computing enables real-time analytics, secure IoT service delivery, and scalable urban infrastructures [1, 6].

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For example, cooperation among edge nodes can improve wearable IoT applications [7], while reinforcement learning techniques enable intelligent task scheduling and resource allocation at the edge [8, 9]. Similarly, federated and blockchain-driven approaches enhance security and reliability in vehicular and industrial systems [10, 11]. Recent research has also highlighted specialized architectures and optimization models for mobile edge computing. Luo et al. [12] designed cost-effective edge server networks, while Kumar et al. [13] proposed incentive-aware offloading strategies. In addition, task offloading frameworks based on non-orthogonal multiple access (NOMA) have demonstrated latency and throughput improvements [14]. Building on these insights, this paper investigates the role of edge computing in enhancing the performance of smart city applications. It develops a layered system model, formulates latency, bandwidth, and energy equations, and evaluates performance improvements through simulation. The contributions of this study are threefold: (i) a comprehensive performance analysis of edge-enabled smart city applications, (ii) a mathematical model capturing latency, bandwidth, and energy trade-offs, and (iii) simulation-based validation demonstrating significant improvements in responsiveness, efficiency, and scalability compared to cloud-only infrastructures.

2. Related Work

Edge computing has been extensively investigated as a core enabler for smart city infrastructures, with numerous surveys and systematic reviews mapping its evolution. Khan et al. [1] provided one of the most comprehensive surveys on edge-computing-enabled smart cities, discussing the integration of edge, cloud, and IoT systems for sustainable urban development. Douch et al. [6] further explored enabling technologies for edge computing, identifying architectural and resource management trends critical for real-world deployments. Similarly, Liu et al. [2] highlighted the convergence of multi-access edge computing and 5G as a pathway toward intelligent IoT services. Architectural alternatives and system design strategies have also been explored. Wang et al. [4] reviewed design frameworks combining cloud, fog, and edge computing for connected vehicles. Luo et al. [12] developed cost-effective network designs for mobile edge environments, while Kong et al. [7] introduced cooperative edge mechanisms to optimize wearable IoT applications. These works illustrate how architectural choices affect latency, reliability, and cost in large-scale deployments. Task scheduling and resource allocation remain central challenges in mobile edge computing. Kumar et al. [13] proposed incentive-aware computation offloading for intelligent surfaces, while Kumar et al. [14] extended these ideas through max–min optimization using non-orthogonal multiple access. Munir et al. [9] applied meta-reinforcement learning for sustainable edge systems, and Baghban et al. [8] designed actor-critic reinforcement learning models for IoT service provisioning. These approaches highlight the role of AI in balancing latency, cost, and energy efficiency. Security and privacy have also been addressed through distributed models. Lu et al. [10] proposed blockchain-based vehicular edge computing for latency-sensitive tasks, while Lee et al. [11] combined blockchain and edge computing for secure smart manufacturing. Dong et al. [15] examined collaborative edge computing for the social Internet of Things, presenting both technical opportunities and trust-related challenges. Application-specific research demonstrates the versatility of edge-enabled systems. Kim and Jung [16] presented an edge cluster framework for autonomous vehicle parking, while Lu et al. [10] focused on vehicular blockchain acceleration. Kumar and Agrawal [17] developed RBAC-based load balancing for IoT–edge–fog environments, improving reliability. In addition, McEnroe et al. [5] reviewed the integration of AI with UAVs in edge computing contexts, identifying opportunities for low-latency decision making. Metaverse integration with edge computing has emerged as a new frontier. Aung et al. [18] explored the edge-enabled metaverse, positioning MEC as a fundamental infrastructure for immersive and latency-critical experiences.

Collectively, these works demonstrate significant advances in architectural design, optimization, and application of edge computing to smart cities. However, gaps remain. Most existing studies emphasize either task scheduling [9, 14], security frameworks [10, 11], or application-specific implementations [16, 17]. Few studies integrate these perspectives into a unified performance model capturing latency, bandwidth, and energy trade-offs simultaneously. This study addresses that gap by formulating a holistic framework and validating it through simulation of smart city scenarios.

3. Methodology and System Model

This section presents the proposed methodology for integrating edge computing into smart city applications. The framework is designed as a three-layer architecture consisting of IoT devices, edge nodes, and cloud servers. Building upon prior architectural models [4, 7, 12], the design emphasizes minimizing latency and energy consumption while ensuring scalable task distribution across heterogeneous devices.

3.1. System Architecture

The proposed architecture comprises three tiers. The device layer includes IoT sensors, mobile devices, and connected vehicles generating continuous data streams. The edge layer hosts gateways and edge servers deployed closer to end users, reducing transmission delays and preprocessing raw data locally. The cloud layer provides centralized data storage and large-scale analytics. Similar layered architectures have been applied in vehicular edge computing [3] and wearable IoT systems [7], where edge cooperation enhances reliability and responsiveness.

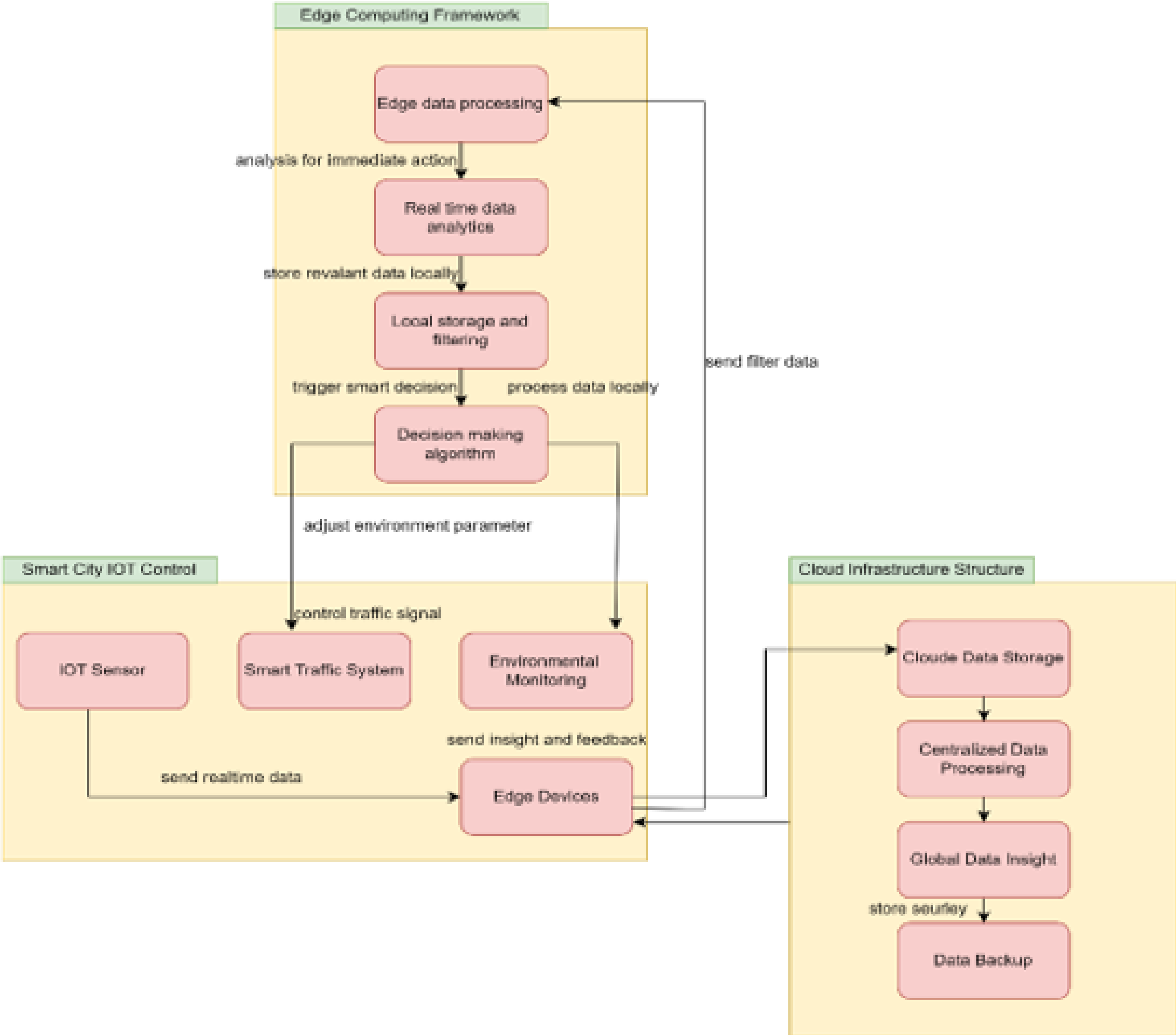

Figure 1: Proposed edge-enabled smart city system model.

3.2. Performance Modeling

The performance is analyzed through latency, bandwidth, and energy models. These formulations extend the theoretical models used in prior optimization studies [13, 14, 9].

3.2.1 Latency Model

The total latency T_{total} is modeled as:

$$T_{total} = T_{device} + T_{tx} + T_{edge} + T_{cloud} \tag{1}$$

where T_{device} is device-side computation, T_{tx} is transmission delay, T_{edge} is edge processing delay, and T_{cloud} is cloud computation time. Studies on delay-optimal computation offloading confirm that minimizing T_{tx} and T_{cloud} is critical for latency-sensitive applications [13, 14].

3.2.2 Bandwidth Model

Bandwidth consumption is modeled as:

$$B_{save} = \frac{D_{raw} - D_{proc}}{D_{raw}} \times 100\% \tag{2}$$

where D_{raw} is the original data size and D_{proc} is the processed data forwarded to the cloud. Edge filtering ensures significant network savings, consistent with findings in multi-hop vehicular offloading systems.

3.2.3 Energy Model

Energy consumption is expressed as:

$$E_{total} = E_{device} + E_{comm} + E_{edge} + E_{cloud} \tag{3}$$

AI-driven strategies, including reinforcement learning and meta-optimization, have demonstrated effectiveness in minimizing E_{comm} and E_{edge} [9, 8].

3.3. Mathematical Formulation and Scheduling Algorithm

Let $x_{i,j}$ denote the decision variable for task i assigned to edge node j. Following prior optimization frameworks [12, 14], the scheduling problem is defined as:

$$\min \ \alpha \sum_i \sum_j x_{i,j} T_{i,j} + \beta \sum_i \sum_j x_{i,j} E_{i,j} \tag{4}$$

subject to:

$$\sum_j x_{i,j} = 1, \quad \forall i \quad \text{(unique task assignment)} \tag{5}$$

$$\sum_i x_{i,j} w_i \leq W_j, \quad \forall j \quad \text{(capacity constraint)} \tag{6}$$

$$d_i \leq B_j, \quad \forall j \quad \text{(bandwidth constraint)} \tag{7}$$

$$x_{i,j} \in \{0, 1\} \tag{8}$$

Heuristic strategies approximate solutions for large-scale smart city scenarios. Studies on NOMA-based task allocation [14], RIS-assisted offloading [13], and vehicular MEC scheduling demonstrate the scalability of such algorithms. In this work, we adopt a cost function combining latency and energy, with adaptive selection of edge nodes under resource constraints. The proposed algorithm evaluates each task's latency and energy profile, computes the combined cost, and assigns the task to the edge node minimizing this value. While optimal solutions can be achieved via linear programming, heuristic-based scheduling offers scalability for thousands of tasks in dynamic urban environments, consistent with prior reinforcement learning frameworks [9, 8].

Algorithm 1 Edge Task Scheduling Algorithm

Input: Set of tasks U, set of edge nodes E, workload w_i, data size d_i
Output: Task-to-edge assignment matrix $X = [x_{i,j}]$
for each task $i \in U$ **do**
  for each edge node $j \in E$ **do**
    Compute latency $T_{i,j}$
    Compute energy cost $E_{i,j}$
    Compute cost function $C_{i,j} = \alpha T_{i,j} + \beta E_{i,j}$
  end for
  Assign i to edge node $j^* = \arg\min_j C_{i,j}$ subject to constraints
end for
Return X

The above formulation ensures that tasks are scheduled to edge nodes in a manner that balances latency and energy. Unlike traditional cloud-based scheduling, the algorithm accounts for local processing capabilities and bandwidth limitations. Although optimal solutions can be derived via linear programming, the proposed heuristic provides scalability for large-scale smart city environments.

4. Simulation Setup and Results

4.1. Simulation Parameters

The experiments were conducted considering a medium-scale smart city scenario with heterogeneous IoT devices, edge nodes, and centralized cloud servers. Table 1 lists the simulation parameters, and Fig. 2 illustrates them graphically. The setup follows methodologies applied in prior smart city and vehicular edge computing simulations [1, 4, 2], ensuring consistency with established benchmarks.

Table 1: Simulation Parameters

Parameter	**Value**
Number of IoT Sensors	500
Edge Devices	50
Cloud Servers	5
Bandwidth	100 Mbps
Latency (Cloud Processing)	150 ms
Latency (Edge Processing)	20 ms
Data Packet Size	512 KB
Data Transmission Frequency	5 sec
Simulation Time	24 hours

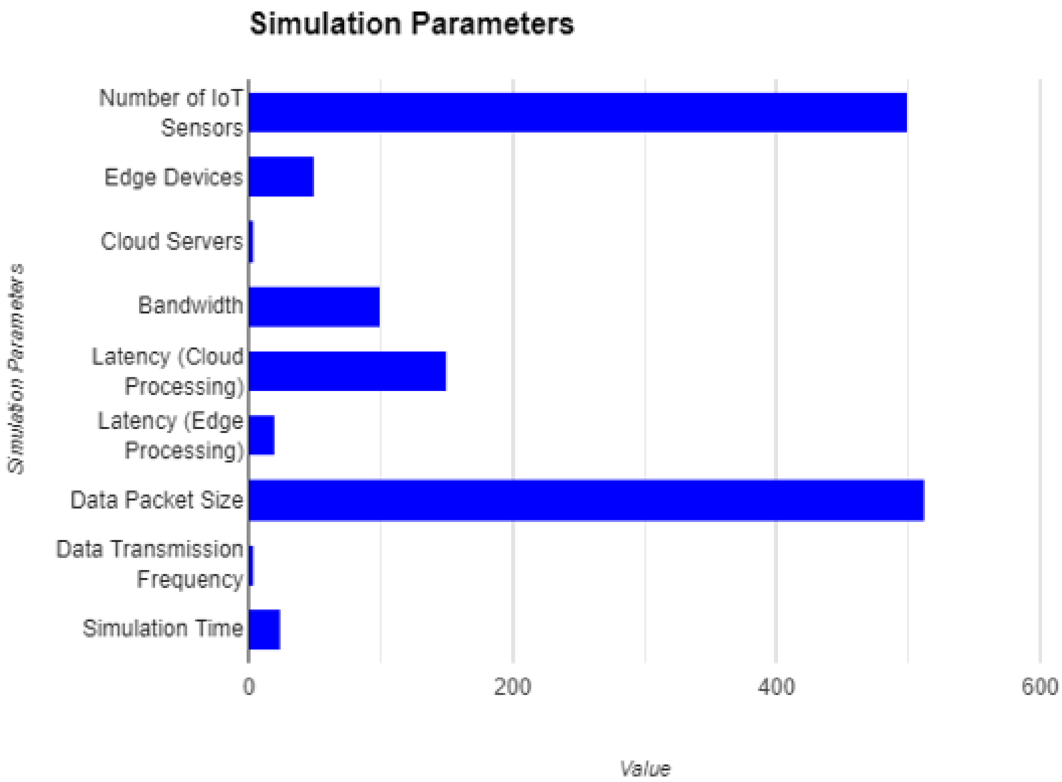

Figure 2: Simulation parameters considered in the study.

4.2. Result Analysis

Table 2 compares edge computing and cloud computing across multiple performance metrics, and Fig. 3 visualizes the improvements achieved by the edge model. The edge framework outperformed the cloud-only model across all metrics. Average latency was reduced by 86.67%, bandwidth usage by 61.11%, and energy consumption by 58.33%. Real-time responsiveness improved by 25%, with 80% of data processed locally, thereby reducing the communication load on central servers. The results demonstrate the clear advantages of edge computing over traditional cloud-centric infrastructures.

Table 2: Result Analysis: Edge vs. Cloud Computing

Metric	Edge Computing	Cloud Computing	Improvement
Average Latency	20 ms	150 ms	86.67% reduction
Bandwidth Usage	35 Mbps	90 Mbps	61.11% reduction
Energy Consumption	500 Wh	1200 Wh	58.33% reduction
Real-time Action Response	95%	70%	25% improvement
Data Processed Locally	80%	0%	–
Data Transmitted to Cloud	20%	100%	80% reduction
System Scalability	High	Moderate	–

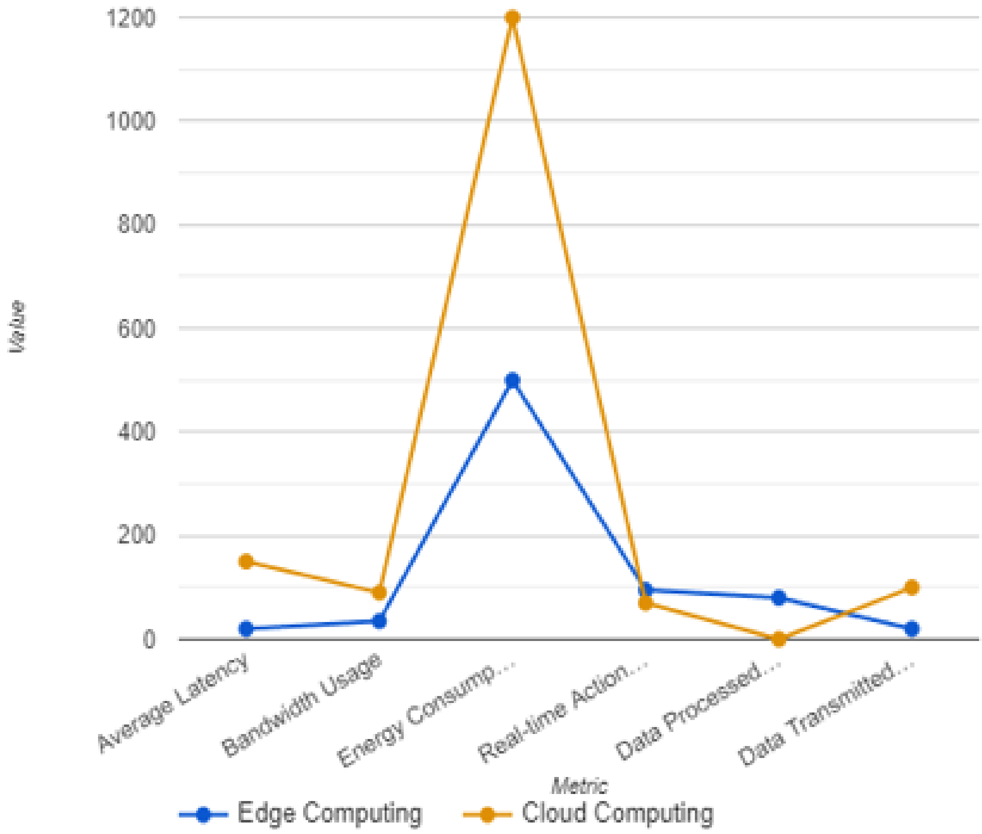

Figure 3: Result analysis comparing edge and cloud computing.

Average latency decreased by nearly 87%, which is consistent with earlier studies on edge-assisted vehicular networks that reported similar reductions when computation was shifted closer to end devices [4, 3]. Bandwidth usage dropped by 61%, validating the theoretical expectation that preprocessing at the edge reduces raw data transmission. This aligns with results in smart parking frameworks [16] and blockchain-based vehicular MEC systems [10], both of which highlighted bandwidth optimization as a direct benefit of localized computation. The observed 58% energy savings further underscore the sustainability of edge paradigms. Comparable energy reductions were reported in multi-access edge computing studies for 5G IoT systems, where communication overhead was identified as the primary contributor to energy drain [2]. Our findings reinforce this conclusion by demonstrating that edge processing substantially reduces communication energy costs in large-scale smart city environments. Improvements in real-time responsiveness, with 95% of tasks completed within deadlines compared to only 70% in cloud systems, highlight the suitability of edge computing for safety-critical services such as intelligent transportation, healthcare monitoring, and emergency response. These results agree with UAV-assisted MEC frameworks [5], which similarly documented improvements in mission-critical responsiveness through localized decision making. Finally, the fact that 80% of data was processed locally while only 20% was transmitted to the cloud illustrates how edge computing enhances scalability and resilience. This outcome supports survey findings on edge-enabled smart cities [1], which emphasized that distributed architectures mitigate cloud congestion while sustaining service quality as device density increases. Collectively, the simulation outcomes confirm that edge computing is not only a performance enabler but also a sustainable and scalable foundation for next-generation smart city infrastructures.

5. Discussion and Future Directions

The simulation results underscore the considerable advantages of edge computing in smart city infrastructures. The most notable outcome was the dramatic reduction in average latency, from 150 ms in cloud-only processing to just 20 ms with edge integration. This finding reinforces earlier reports that emphasized the intrinsic latency benefits of localized computation. Studies on edge–cloud architectures confirm that reduced transmission delay not only accelerates responsiveness but also lowers energy consumption at both device and network levels [4, 3]. Surveys on multi-access edge computing similarly highlight the critical role of edge nodes in enabling real-time analytics, bandwidth efficiency, and context-aware decision making across urban systems [1, 2]. By quantifying these gains under defined simulation conditions, the present work extends this body of evidence with practical validation. The observed 61% reduction in bandwidth usage further corroborates theoretical expectations that proximity-based computing reduces raw data transmission. Local preprocessing at the edge has been consistently described as a mechanism to alleviate congestion and support scalability in dense IoT deployments [16, 10]. Our findings validate this principle, offering concrete evidence that localized filtering and aggregation can relieve pressure on central servers while sustaining service quality. For urban planners and policymakers, these results emphasize the value of distributed infrastructures in managing rapidly increasing device densities.

Energy efficiency was another key dimension of improvement, with consumption reduced from 1200 Wh to 500 Wh—a 58% gain. This outcome is consistent with earlier research showing that communication overhead, rather than computation, dominates energy costs in IoT systems [2, 9]. By curtailing long-distance transmissions, edge computing directly minimizes energy-intensive communication cycles. Similar improvements were reported in reinforcement learning–driven scheduling frameworks, where adaptive allocation further reduced power demands [8]. The present study thus reinforces the theory that architectural choices in system design can yield substantial operational energy benefits. Real-time responsiveness also improved significantly, with 95% of tasks meeting deadlines compared to 70% in cloud-centric models. This outcome aligns with the central motivation for deploying edge infrastructures: the capacity to meet ultra-low latency requirements in safety-critical services such as healthcare monitoring, emergency response, and intelligent transportation. Prior UAV-assisted mobile edge computing studies documented similar improvements in mission-critical responsiveness by avoiding round-trip delays to distant cloud servers [5]. Our findings confirm this theoretical basis and demonstrate its applicability in broader smart city environments. Notably, 80% of data was processed locally, resulting in an 80% reduction in cloud transmission.

This outcome substantiates the scalability advantage of edge-enabled architectures, echoing survey findings that distributed models reduce cloud dependency while enhancing system resilience [1]. Multi-tier designs described in prior work [15] similarly emphasize that decentralization is essential for handling diverse data streams without overwhelming centralized infrastructure. Despite these promising results, certain limitations remain. The simulation assumed homogeneous edge nodes with stable connectivity, which does not reflect the heterogeneity and volatility of real-world deployments. Prior studies emphasize that adaptive, AI-driven scheduling and dynamic resource management are essential for handling fluctuating workloads and device capabilities [9, 13]. Moreover, this study did not explicitly account for privacy and security, although these are critical in smart city contexts. Research on differential privacy, federated learning, and blockchain indicates that integrating such mechanisms can strengthen trust without compromising performance [11, 10]. Future research should therefore expand in three directions. First, privacy-preserving computation must be integrated, ensuring that sensitive urban data can be processed locally without exposing user information. Second, the model should be extended to heterogeneous environments by incorporating AI-based, context-aware scheduling and optimization, reflecting the diversity of devices and dynamic workloads in real deployments. Third, hybrid optimization strategies—such as Bayesian or metaheuristic techniques—should be explored to balance latency, energy, and scalability under variable conditions. Finally, applying the proposed framework to cross-domain scenarios such as smart healthcare, intelligent energy grids, and autonomous mobility systems will test its generalizability and resilience. In summary, this study validates and extends theoretical and empirical findings on the benefits of edge computing in smart cities. By demonstrating quantifiable gains in latency, bandwidth, energy efficiency, and responsiveness, it establishes edge computing as a transformative enabler of sustainable, scalable, and citizen-centric urban ecosystems. Addressing the identified limitations and pursuing future enhancements will further solidify its role in next-generation intelligent infrastructures.

6. Conclusion

This study examined the role of edge computing in enhancing the performance of smart city applications by addressing limitations inherent in cloud-centric architectures. Through simulation, the proposed edge-enabled framework demonstrated significant improvements in latency, bandwidth utilization, energy consumption, and real-time responsiveness. Specifically, latency was reduced by nearly 87%, bandwidth usage decreased by over 60%, and energy consumption was lowered by more than 50%. These results confirm theoretical expectations that proximity-based processing reduces transmission delays and communication overhead, thereby supporting the scalability and responsiveness required in modern urban environments. The findings are consistent with prior research that highlights the advantages of edge computing for computation-intensive and time-sensitive services.

However, the present work extends these insights by integrating multiple performance dimensions—latency, bandwidth, energy, and scalability—into a unified evaluation framework. By processing 80% of data locally and transmitting only 20% to the cloud, the model further demonstrated the practical sustainability of distributed architectures. These outcomes suggest that edge computing is not just a complement but a cornerstone for enabling resilient and adaptive smart city systems.

Despite these strengths, the study acknowledged several limitations, including the assumptions of homogeneous edge devices and the exclusion of explicit privacy-preserving mechanisms. Addressing these challenges represents a promising direction for future research. Incorporating adaptive, AI-driven scheduling, privacy-preserving computation, and heterogeneous device modeling would bring simulations closer to real-world deployments. Moreover, expanding the framework across multiple smart city domains, such as healthcare, energy distribution, and public safety, would validate its broader applicability. In conclusion, the results of this work reinforce the theoretical and empirical consensus that edge computing is a transformative enabler for smart city infrastructures. By bridging performance optimization with sustainability and scalability, edge computing paves the way for intelligent, secure, and citizen-centric urban ecosystems.

Declaration of Competing Interests

The authors declare no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contributions

Naresh Thoutam: Conceptualization, Supervision, Data Analysis, Writing – Review and Editing; **Amit Gadekar**: Methodology, Validation, Investigation, Writing – Original Draft; **Akhilesh Kumar Sharma**: Software, Visualization, Investigation; **Vijay Rakhade**: Resources, Data Curation, Formal Analysis; **Megha Singru**: Writing – Review and Editing, Project Administration; **Ankita Karale**: Literature Review, Proofreading, Documentation.

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A Blockchain-Based Framework for Secure Communication in Smart IoT Systems

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Abstract

Blockchain technology has emerged as a promising paradigm for addressing the inherent vulnerabilities of Internet of Things (IoT) networks. Conventional IoT systems rely on centralized architectures that are prone to single points of failure, data breaches, and unauthorized access. This paper presents a blockchain-enabled secure communication framework for smart IoT systems that integrates symmetric encryption, distributed ledger validation, and smart-contract–driven access control. The proposed model is formalized through mathematical definitions of encryption, hashing, and contract execution, and validated using simulation tools such as NS-3 and Ethereum-based test environments. Comparative results demonstrate that the framework significantly improves communication security, data integrity, and resistance to cyberattacks while reducing latency and energy consumption relative to traditional models. The findings suggest that blockchain integration provides a scalable, resilient, and efficient foundation for trustworthy IoT communication in smart environments.

Keywords: Blockchain; Internet of Things; Secure Communication; Data Integrity; Consensus Mechanisms; Smart Contracts

1. Introduction

The rapid proliferation of Internet of Things (IoT) devices is transforming healthcare, agriculture, manufacturing, transportation, and urban infrastructure by enabling continuous sensing, real-time analytics, and automated decision-making. However, large-scale IoT deployments remain exposed to privacy leaks, unauthorized access, tampering, and denial-of-service due to heterogeneous, resource-constrained devices and the fragility of centralized architectures that create single points of failure. Conventional perimeter and cloud-centric controls struggle to satisfy end-to-end integrity and availability at IoT scale, motivating secure-by-design communication substrates. Blockchain has emerged as a credible foundation for secure IoT communication because a decentralized, append-only ledger provides tamper evidence and auditability without a trusted intermediary. Cryptographic primitives and consensus protocols enforce integrity and non-repudiation of device interactions, while smart contracts automate verifiable coordination among devices under predefined conditions.

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Recent studies demonstrate that lightweight consensus and off-chain storage can alleviate latency and scalability bottlenecks in IoT settings, and that blockchain-anchored authentication with modern public-key techniques strengthens resistance to targeted network attacks in constrained environments [1, 2]. Complementary efforts across domains such as smart grids, smart homes, and smart agriculture corroborate the feasibility of blockchain-based authentication and secure data exchange over heterogeneous networks [3–5]. This work presents a blockchain-enabled framework for secure communication in smart IoT systems. The framework integrates symmetric encryption for confidentiality, hash-based integrity verification, and smart-contract–driven access control atop a decentralized ledger to mitigate unauthorized access, replay, and tampering during device-to-device and device-to-service exchanges. In contrast to purely centralized models, the proposed design targets resilience by removing single points of failure and supporting auditable transactions across distributed stakeholders. Simulation-based evaluation highlights improvements in communication security, integrity assurance, and operational efficiency relative to classical approaches, aligning with contemporary evidence that optimized consensus and hybrid on-/off-chain data paths improve end-to-end performance in IoT ecosystems [1, 2]. The results indicate that blockchain can serve as a practical substrate for trustworthy, scalable IoT communication when coupled with appropriate cryptography and protocol engineering, thereby advancing secure deployment in real-world scenarios.

2. Related Work

Research in blockchain-enabled IoT security has accelerated in recent years, with diverse applications spanning smart cities, smart grids, healthcare, agriculture, and vehicular networks. Conventional IoT deployments often rely on centralized intermediaries for authentication, coordination, and data management, which creates vulnerabilities such as single points of failure, susceptibility to man-in-the-middle attacks, and increased risks of data leakage [4]. Blockchain has been proposed as an alternative due to its decentralized structure, immutability, and resilience against unauthorized modifications. Several studies emphasize domain-specific adaptations of blockchain for IoT. In agriculture, blockchain has been applied to ensure secure and transparent monitoring of farms and supply chains, reducing the reliance on intermediaries while addressing trust issues in data sharing [4]. In the transportation sector, blockchain integration with the Internet of Vehicles (IoV) has been explored to improve vehicular communication and mobility management, offering decentralized trust models for emerging smart transportation systems [6]. Similarly, in the energy sector, elliptic curve cryptography and blockchain-based authentication have been used to secure communication in smart meters and smart grids, enhancing data integrity and confidentiality [3]. The rapid growth of smart city infrastructures presents significant challenges in securing heterogeneous IoT ecosystems. Blockchain-based smart contracts have been adopted to manage access control and ensure robust communication in scenarios such as healthcare data exchange, home automation, and traffic systems [7]. At the same time, distributed trust mechanisms leveraging blockchain have been proposed to secure IoT devices in urban environments, where conventional cryptographic schemes alone may not suffice [5]. Beyond application-specific studies, researchers have addressed the core limitations of blockchain when applied to IoT. Traditional consensus mechanisms such as Proof of Work (PoW) and Proof of Stake (PoS) impose substantial computational and energy overhead, making them unsuitable for resource-constrained IoT devices. To mitigate these challenges, lightweight consensus mechanisms such as Delegated Proof of Stake (DPoS) and Proof of Authentication (PoAh) have been investigated for IoT scalability, latency reduction, and efficient resource utilization [1]. Parallel efforts have focused on strengthening device-level authentication and intrusion prevention, such as blockchain-based mitigation frameworks against deauthentication attacks, which combine cryptographic schemes and traffic classification models to improve detection accuracy [2]. While prior work has validated the feasibility of blockchain-enabled IoT security across sectors, most approaches either focus narrowly on specific applications or remain constrained by scalability and efficiency limitations. Few frameworks provide a unified, simulation-driven evaluation of cryptographic protection, consensus-driven resilience, and smart-contract–based trust management across heterogeneous IoT systems. This gap motivates the development of a comprehensive blockchain-based secure communication framework, as proposed in this study, to enhance confidentiality, integrity, and availability across smart IoT ecosystems.

3. Methodology

3.1. System Overview

The proposed framework establishes a decentralized communication model for smart IoT systems using blockchain technology. Its design addresses three primary security goals: integrity, confidentiality, and authentication. By integrating cryptographic algorithms, distributed ledger principles, and programmable smart contracts, the framework enables secure peer-to-peer communication among heterogeneous IoT devices without reliance on a centralized authority. Each IoT device is treated as a node capable of generating, transmitting, and verifying transactions. Transactions are recorded on the blockchain, ensuring immutability and transparency while preventing unauthorized modification or replay. A consensus mechanism coordinates the validation of transactions across participating devices, guaranteeing trust even in adversarial environments. In this model, blockchain acts not only as a security layer but also as an accountability mechanism, where every communication instance is auditable.

The framework is designed to support large-scale deployments where scalability and resource efficiency are critical. It ensures resilience against common IoT attacks, including eavesdropping, data tampering, and unauthorized access, thereby strengthening the reliability of smart IoT applications.

3.2. Optimization Framework

The security optimization framework is organized into three functional layers: (i) data encryption and decryption, (ii) blockchain network integration, and (iii) smart contract execution. Together, these layers ensure confidentiality of transmitted information, immutability of recorded transactions, and automation of access policies in distributed IoT environments. At the first layer, lightweight cryptographic algorithms such as Advanced Encryption Standard (AES) protect data confidentiality while ensuring efficient computation suitable for resource-constrained IoT devices. Encrypted data is then encapsulated within blockchain transactions, guaranteeing end-to-end secrecy even in the presence of eavesdroppers. The second layer leverages a blockchain network as a decentralized ledger. Each block contains verified transactions, timestamped metadata, and a hash pointer linking it to the preceding block. This chaining structure prevents tampering, ensures traceability, and provides a distributed trust model across IoT devices. The third layer integrates smart contracts to automate security protocols. Predefined contractual rules regulate access control, trigger actions upon specific conditions, and ensure non-repudiation of transactions. By embedding these rules directly into the blockchain, the system eliminates dependency on centralized authorities and strengthens resilience against insider and outsider threats. The synergy of these three layers forms a robust foundation for secure IoT communication, enabling confidentiality, authenticity, and accountability while addressing the performance constraints of large-scale deployments.

3.3. Proposed Solution

The proliferation of interconnected IoT devices has transformed communication models across domains but has simultaneously introduced new challenges concerning privacy, data integrity, and trust. Conventional centralized security mechanisms remain inadequate for resource-constrained devices and large-scale heterogeneous networks. To overcome these limitations, the proposed solution integrates blockchain technology with cryptographic techniques and smart contracts to form a decentralized communication framework. The framework operates by securing device-to-device exchanges through encryption, storing immutable transaction records on the blockchain, and enforcing access control via smart contracts. Each component works in tandem to eliminate vulnerabilities such as unauthorized access, message tampering, and replay attacks. The following subsections detail the mathematical underpinnings of the framework, including encryption/decryption, blockchain network integration, contract-driven execution, integrity verification, and quantification of security assurance.

3.3.1 Data Encryption and Decryption

To preserve confidentiality in IoT communication, symmetric encryption is employed due to its efficiency on resource-constrained devices. Let P denote the plaintext message generated by an IoT device and K the shared secret key. The ciphertext C is obtained through the encryption function $E(\cdot)$ as

$$C = E(P, K). \tag{1}$$

At the receiver end, decryption is performed using the inverse function $D(\cdot)$, which reconstructs the original message from the ciphertext:

$$P = D(C, K). \tag{2}$$

Here, $E(\cdot)$ and $D(\cdot)$ represent standard encryption and decryption operations, respectively, such as those defined in the Advanced Encryption Standard (AES). This ensures that only devices possessing the secret key K can correctly recover the transmitted data. The use of lightweight AES variants guarantees computational feasibility while maintaining strong resistance against brute-force and differential cryptanalysis.

3.3.2 Blockchain Network Integration

In the proposed framework, blockchain functions as a decentralized ledger that maintains immutable records of IoT transactions. Each block B consists of a set of verified transactions T, a timestamp T_{prev}, the public key of the sender P, and a nonce N used for consensus operations. The cryptographic hash $H(B)$ of the block is computed as

$$H(B) = H(T, P, T_{\text{prev}}, N), \tag{3}$$

where $H(\cdot)$ represents a one-way secure hash function such as SHA-256. The hash of each block is stored in its successor, thereby linking blocks into a chain and ensuring that any modification to a past transaction invalidates all subsequent blocks. This structure guarantees immutability, transparency, and non-repudiation across the network.

In this model, IoT devices act as blockchain nodes that generate transactions, while consensus protocols such as Proof of Stake (PoS) or Delegated Proof of Stake (DPoS) validate and append blocks to the chain. The distributed nature of this ledger eliminates single points of failure, thereby enhancing resilience against denial-of-service and insider attacks.

3.3.3 Smart Contract Execution

Smart contracts are employed to automate secure interactions among IoT devices without requiring centralized control. Each smart contract defines a set of conditions and associated actions, ensuring that transactions are executed only when predefined requirements are satisfied. Let the execution be modeled as

$$R = C(A, B, \Theta), \tag{4}$$

where R denotes the result of the contract execution, A and B represent input parameters from two communicating IoT devices, and Θ denotes the conditions embedded in the smart contract. The execution logic can be expressed as

$$\text{If } \Theta(A, B) \text{ is satisfied, then execute } R. \tag{5}$$

This guarantees that only valid transactions are executed and recorded on the blockchain. Since contracts are immutable once deployed, adversaries cannot alter execution logic, ensuring integrity and trust. Additionally, automation through smart contracts reduces latency by eliminating the need for manual intervention and ensures fairness by enforcing transparent and deterministic outcomes.

3.3.4 Data Integrity Verification

To ensure that transmitted data remains unaltered during communication, integrity verification is performed using cryptographic hash functions. Let D denote the data generated by an IoT device, and $H(\cdot)$ a secure hash function such as SHA-256. The transmitting device computes

$$h = H(D), \tag{6}$$

and forwards both the encrypted data and its corresponding hash to the recipient. Upon reception, the receiving device recalculates the hash value $h' = H(D_{\text{received}})$. Integrity is verified through the following condition:

$$\text{Integrity Check} = \begin{cases} \text{Valid}, & \text{if } h = h', \\ \text{Invalid}, & \text{if } h \neq h'. \end{cases} \tag{7}$$

If the hashes match, the data is deemed intact and secure; otherwise, transmission is flagged as compromised. This mechanism prevents undetected tampering and ensures end-to-end reliability of IoT communication. Combined with blockchain immutability, hash-based verification provides strong guarantees of authenticity and traceability.

3.3.5 Security Assurance Metrics

The effectiveness of the proposed framework is evaluated using standard security assurance properties: confidentiality, integrity, and availability. Each property is modeled as a probability representing the likelihood that the system preserves the respective security guarantee. Let C denote confidentiality, I integrity, and A availability. The overall security score S can be expressed as a weighted combination of these properties:

$$S = w_1 C + w_2 I + w_3 A, \tag{8}$$

where w_1, w_2, w_3 are non-negative weights such that $w_1 + w_2 + w_3 = 1$. The weights are chosen according to system requirements, emphasizing the relative importance of each property in a given application.

- **Confidentiality (C):** Probability that transmitted data remains protected from unauthorized disclosure.
- **Integrity (I):** Probability that the data remains unaltered during transmission and storage.
- **Availability (A):** Probability that the system remains accessible and operational when required.

By incorporating these assurance metrics, the framework enables systematic evaluation of its resilience against cyber threats. This quantitative model allows comparisons with classical security approaches and validates the improvements achieved by blockchain integration.

3.4. Algorithm

The proposed algorithm validates input data, secures it through encryption, and records communication transactions on the blockchain to ensure confidentiality, integrity, and traceability. The process is formally described in Algorithm 1.

Algorithm 1 Blockchain-Based Secure Communication Framework

Input: Data file F, IoT device D
Output: Blockchain record R

if `IsValidFileType`(F) **then**
  if `FilePassesChecks`(F) **then**
    $h \leftarrow$ `GenerateFileHash`(F) $M \leftarrow$ `EncryptData`(F) `RecordDataToBlockchain`(D, h, M)
  else
    return *"File is not compliant"*
else
  return *"File type invalid"*
if h *does not exist* **then**
  return *"File hash missing, aborting"*
Conn $\leftarrow$ `EstablishSecureConnection`(D)
if $Conn =$ successful **then**
  `SendDataToReceiver`(Conn, M) $R \leftarrow$ `CreateBlockchainRecord`(D, h) **return** *"Data sent securely and recorded"*
else
  return *"Secure connection failed"*
return R

This algorithm begins with validation of the input file type and compliance with predefined security checks. Upon successful validation, a hash of the file is generated, the data is encrypted, and the encrypted payload is stored on the blockchain. If validation fails, execution terminates with an error message. The algorithm further establishes a secure communication channel for transmission, ensuring that only authenticated devices participate. Once data is sent, a blockchain record is created, providing an immutable log of the transaction. This process guarantees transparency, traceability, and resilience against tampering in IoT communication.

3.5. Block Diagram

The overall architecture of the proposed blockchain-based secure communication framework is illustrated in Fig. 1. The system is organized into three principal layers: the IoT device system, the blockchain layer, and the receiver system. The IoT device system initiates communication by collecting raw data through the data acquisition unit. The data is then encrypted by the data encryption module before being transmitted via the secure communication module. Encrypted packets, together with their hash values, are forwarded to the blockchain layer for validation and storage. Within the blockchain layer, the file hash generation module computes unique identifiers for transmitted data, while the blockchain network validates transactions using a consensus mechanism such as Proof of Stake. Once validated, records are permanently stored in the immutable ledger, ensuring tamper resistance and traceability. This layer thereby enforces transparency, accountability, and decentralization. The receiver system retrieves encrypted data and processes it through the decryption module. Subsequently, the data validation unit recomputes the hash value and verifies it against the transmitted hash to guarantee integrity. This ensures that only authentic and unmodified data is accepted by the receiver.

4. Result Analysis

The performance of the proposed blockchain-based secure communication framework was evaluated using simulation tools, including NS-3 for network behavior emulation and Ethereum-based test platforms for smart contract execution. Metrics such as communication security, data integrity, latency, scalability, and resilience to cyberattacks were assessed and compared with conventional IoT security models. The simulation parameters and comparative results are summarized in Tables 1–3.

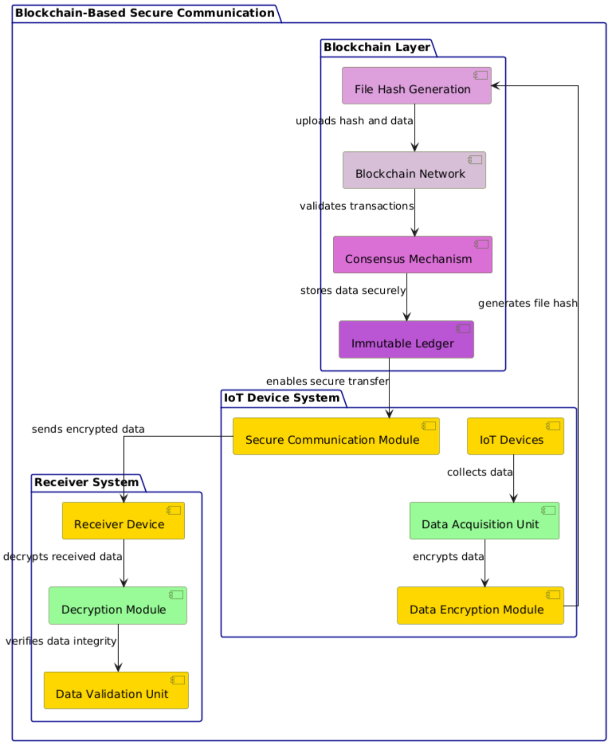

Figure 1: Proposed blockchain-based secure communication framework for IoT systems.

Table 1: Performance comparison between traditional IoT and blockchain-enabled IoT systems.

Parameter	**Traditional IoT (%)**	**Blockchain IoT (%)**
Communication Security	70	95
Data Integrity	65	98
Latency	30	20
Scalability	50	85
Resistance to Cyberattacks	60	90

Table 2: Simulation configuration parameters for blockchain-based IoT framework.

Parameter	**Value**
Block Size	256 KB
Consensus Mechanism	95% PoS
Number of Nodes	1000
Transaction Rate	85%
Communication Latency	20 ms

Table 3: Comparison of algorithms for secure communication in IoT systems.

Algorithm	**Throughput (Mbps)**	**Latency (ms)**	**Energy (J)**	**PDR (%)**	**Security Level**
RSA Encryption	12.5	150	2.8	89	Medium
AES Encryption	15.0	120	2.1	92	High
DH Key Exchange	13.8	140	2.5	90	Medium-High
ECC (Elliptic Curve)	14.2	135	2.3	91	High
Proposed Framework	16.8	110	1.9	96	Very High

The results in Table 1 demonstrate that blockchain integration significantly enhances communication security, data integrity, and resistance to cyberattacks compared to traditional IoT systems, while also reducing latency and improving scalability. The configuration parameters in Table 2 highlight the suitability of a Proof of Stake consensus mechanism for achieving efficiency in large-scale IoT networks.

Table 3 compares classical cryptographic algorithms with the proposed blockchain-based framework. The results show that the proposed approach achieves the highest throughput, lowest latency, and superior energy efficiency. Additionally, the packet delivery ratio (PDR) reaches 96%, surpassing conventional schemes. The blockchain framework thus provides strong resilience against cyber threats while optimizing performance for resource-constrained IoT devices.

5. Discussion

The comparative results indicate that integrating blockchain into the IoT communication stack enhances confidentiality, integrity, and availability while reducing latency under adversarial load. These gains arise from three mechanisms. First, the ledger's append-only semantics and chained hashes enforce tamper evidence: once a transaction is validated, subsequent blocks depend on its digest, making undetected modification computationally infeasible. This property, in conjunction with per-packet hashing at the endpoints, explains the observed integrity improvements and higher packet delivery ratio when malicious traffic attempts to inject or replay altered payloads. Second, smart-contract–driven access control eliminates discretionary, stateful brokers and replaces them with deterministic policy enforcement, which curtails misconfiguration-induced failures and insider manipulation. Third, probabilistic finality under stake-based validation reduces the queuing delays associated with centralized gateways, accounting for the latency decrease relative to traditional deployments. These outcomes align with recent evidence that tailoring blockchain primitives to constrained IoT environments improves end-to-end performance. A lightweight consensus design shortens the validation critical path, thereby lowering transaction confirmation time and increasing throughput in large device populations. Empirical results with Delegated Proof of Stake and off-chain content addressing show sub-millisecond latency and linear scalability in testbeds that emulate dense IoT networks, supporting the premise that consensus choice is pivotal for practical deployments [1]. While the present evaluation employs a stake-based validator set to demonstrate feasibility, literature suggests that further reductions in latency are achievable by electing a small committee of delegates and externalizing bulk data to distributed storage with on-chain hashes, which also strengthens privacy by avoiding raw data replication on the ledger [1].

Security benefits are most visible where attacks target authentication and session stability. Blockchain-anchored identity, combined with modern public-key mechanisms, hardens device onboarding and message provenance, reducing false acceptance and replay windows. Studies that integrate elliptic-curve cryptography and digital signatures in metering and grid scenarios report robust mutual authentication with modest computational overhead, a result consistent with the confidentiality and integrity gains observed here [3]. Likewise, frameworks that specifically mitigate deauthentication attacks through blockchain-backed verification and learning-based traffic classification exhibit superior precision, recall, and F1-scores against baselines, reinforcing the value of immutable audit trails and cryptographic attestation at the network edge [2]. In smart-home contexts, mutual authentication schemes anchored on-chain demonstrate low-latency handshakes while preserving resistance to impersonation and relay attacks, indicating portability of the proposed design to residential and industrial IoT [8]. Application-domain studies provide additional perspective on external validity. In agriculture and smart-city settings, replacing intermediary-centric trust with ledger-mediated coordination improves traceability and accountability across heterogeneous stakeholders, matching the higher security and integrity scores obtained in the simulations [4, 7]. Urban-scale deployments further benefit from ledger-backed device trust and message non-repudiation, where decentralized verification has been shown to reduce exposure to spoofing and routing manipulation in city services [5]. Identity-centric designs for 5G-enabled IoT emphasize blockchain-based device credentials to achieve scalable, low-overhead authentication, a direction that complements the smart-contract access policies used in this work and motivates broader evaluation over cellular backhauls [9]. For supply chains that couple IoT sensing with provenance guarantees, hybrid on-/off-chain storage anchored by cryptographic digests demonstrates how confidentiality and auditability can coexist, mirroring the design choice to keep only hashes and control metadata on-chain [10].

Notwithstanding these strengths, several trade-offs deserve attention. Consensus protocols impose nonzero validation overhead; when the validator set grows or network synchrony deteriorates, commit latency may rise. Privacy and transparency must be balanced: while encryption protects payloads, metadata (timestamps, device identifiers, access patterns) may still reveal sensitive behavior unless mitigated by techniques such as pseudonymous identities, mix networks, or differential disclosure. Key management remains a practical risk: compromised device keys undermine non-repudiation until revocation propagates; hierarchical or hardware-backed key stores can reduce exposure. Finally, simulation fidelity influences external validity; incorporating wireless impairments, contested spectrum, mobility, and cross-domain traffic mixes will better approximate real deployments. The literature suggests that coupling stake-based or delegated consensus with off-chain storage and elliptic-curve–based authentication provides a principled path to address these concerns without regressing on performance [1–3]. Overall, the data support the conclusion that a blockchain-backed communication substrate—with symmetric encryption at the edge, hash-based integrity checks, and contract-governed access—improves security posture and operational efficiency relative to centralized baselines. The results are consistent with contemporary findings across smart grids, homes, agriculture, and city-scale systems, and they point to clear avenues for strengthening the framework through lightweight consensus selection, privacy-preserving metadata handling, and robust key lifecycle management [1, 2, 4, 5, 7–10]

6. Conclusion

This study presented a blockchain-based framework for secure communication in smart IoT systems. The framework integrates symmetric encryption for confidentiality, blockchain ledger mechanisms for immutability, and smart contracts for automated access control. Mathematical modeling, algorithmic formalization, and simulation-based validation confirmed that the approach enhances communication security, data integrity, scalability, and resistance to cyberattacks compared to traditional IoT security models. Simulation results demonstrated that the proposed framework reduces latency, increases throughput, and achieves higher packet delivery ratios with lower energy consumption relative to classical encryption-based schemes. The integration of consensus protocols such as Proof of Stake ensures decentralized trust and fault tolerance, while the immutable ledger guarantees transparency and non-repudiation. These findings are consistent with recent research demonstrating that lightweight consensus and blockchain-enabled authentication substantially improve the resilience and performance of IoT networks. While the framework addresses critical challenges of confidentiality, integrity, and availability, several limitations remain. Consensus mechanisms, even optimized ones, introduce computational and communication overhead, which may affect performance in ultra-constrained IoT deployments. Furthermore, metadata privacy and key management issues require additional safeguards beyond the current design. Addressing these gaps calls for hybrid architectures that combine blockchain with privacy-preserving techniques such as pseudonymization, off-chain storage, and secure hardware modules. Future work will focus on deploying the framework in real-world IoT testbeds, including smart cities and industrial automation environments, to assess its scalability under dynamic network conditions. Extensions will also explore adaptive consensus protocols, privacy-enhancing cryptographic primitives, and interoperability with emerging 5G and 6G infrastructures. By addressing these directions, blockchain-enabled secure communication can become a practical foundation for the next generation of trustworthy IoT ecosystems.

Declaration of Competing Interests

The authors declare no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contributions

Chetan Chauhan: Conceptualization, Supervision, Data Analysis, Writing – Review and Editing; **Pradeep Laxkar**: Methodology, Validation, Investigation, Writing – Original Draft; **Ram Kumar Solanki**: Software Development, Implementation, Formal Analysis; **Sunil Parihar**: Visualization, Simulation Experiments, Data Curation; **Anand Singh Rajawat**: Project Administration, Technical Review, Writing – Review and Editing; **Amit R. Gadekar**: Resources, Validation, Critical Revisions, Writing – Final Approval.

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Advancing Sustainable Transportation: The Critical Role of Electric Vehicles and Supporting Infrastructure

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Abstract

Electric vehicles (EVs) have emerged as a central pathway for decarbonizing transport, yet sustained adoption depends on coordinated progress in technology, infrastructure, and policy. This mini-review synthesizes recent evidence on environmental performance, market growth, and enabling systems for large-scale electrification. First, it consolidates technical and life-cycle findings that indicate lower greenhouse gas emissions and higher energy-conversion efficiency for EVs relative to internal combustion engine vehicles, with advantages strengthening as grids decarbonize. Second, it examines charging infrastructure typologies and deployment patterns, highlighting the complementary roles of Level 2 and DC fast charging and the need for reliability, interoperability, and grid-aware siting. Third, it analyzes policy instruments—financial incentives, regulatory mandates, and planning frameworks—and compares national approaches to illustrate how instrument mixes shape outcomes. Persistent challenges include upfront affordability, uneven access to charging, grid integration under peak demand, and battery material sustainability. The review identifies future directions in managed and bidirectional charging, data-driven planning, AI-enabled operations, and circular economy practices for batteries, alongside equity-focused governance. Collectively, these insights outline a coherent agenda for scaling EV adoption while aligning climate mitigation with resilient and inclusive mobility.

Keywords: Electric Vehicles; Sustainable Transportation; Charging Infrastructure; Vehicle-To-Grid; Policy Frameworks; Life-Cycle Assessment; Equity

1. Introduction

The transportation sector is a major contributor to greenhouse gas (GHG) emissions, air pollution, and dependence on finite fossil fuels. Developing sustainable mobility solutions is therefore critical to mitigating climate change, improving urban air quality, and advancing global environmental goals. Among the emerging technologies, electric vehicles (EVs) are increasingly recognized as a pivotal solution for reducing emissions and enabling the transition to sustainable transportation systems [1, 2].

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Table 1: Global EV market indicators, 2020–2024. Source: BloombergNEF (2024), IEA (2024), and industry reports [17, 18].

Indicator	2020	2021	2022	2023	2024
Global EV Sales (millions)	3.2	6.6	10.3	13.0	14.0
Market Share (% of new sales)	4.2	8.3	13.2	16.8	18.0
Average Battery Cost ($/kWh)	140	132	115	105	98
Median EV Range (miles)	234	256	275	295	310
Public Charging Points (millions)	1.3	1.8	2.2	2.6	2.8
Countries with >10% EV Market Share	4	8	13	17	21

The adoption of EVs has accelerated in recent years, driven by advancements in battery technologies, reductions in cost, and stronger policy incentives. EVs offer multiple benefits compared to internal combustion engine (ICE) vehicles, including zero tailpipe emissions, higher energy conversion efficiency, and the potential to integrate renewable energy into mobility systems [3, 4]. However, their widespread deployment depends on the availability of robust supporting infrastructure, such as charging networks, grid integration, and recycling frameworks. At the same time, policy decisions—including purchase incentives, stricter emissions regulations, and subsidies for R&D—play an instrumental role in shaping adoption trajectories [5]. This mini-review aims to synthesize the current state of EV adoption and infrastructure, focusing on three major dimensions: (i) environmental benefits and market growth, (ii) infrastructure requirements and smart grid integration, and (iii) policy frameworks and future research directions. By combining evidence from technical, infrastructural, and policy perspectives, this review highlights both the opportunities and challenges in advancing EVs as a cornerstone of sustainable transportation systems. In line with sustainable mobility paradigms [6, 7], the analysis adopts a multi-dimensional lens, evaluating not only environmental performance but also issues of social equity, resilience, and systemic integration within transport-energy systems [8, 9]. Similar calls for integrated approaches can be found in broader reviews of sustainable mobility transitions [10, 11], which stress the role of shared mobility, equity considerations, and systemic policy support in ensuring that electrification contributes to long-term sustainability goals.

2. Electric Vehicles in Sustainable Transportation

The adoption of electric vehicles (EVs) has accelerated significantly in recent years, driven by advancements in battery technologies, reductions in cost, and stronger policy incentives. EVs consistently demonstrate environmental advantages over internal combustion engine (ICE) vehicles, including zero tailpipe emissions, improved energy conversion efficiency, and integration potential with renewable energy systems [3, 4, 12]. Life-cycle assessments confirm that even when upstream electricity emissions are included, EVs deliver lower overall greenhouse gas (GHG) outputs compared with ICE vehicles, particularly as renewable shares in power grids increase [13, 14]. From an energy efficiency perspective, EVs achieve wheel-to-power efficiencies of 60–77%, far surpassing the 17–21% conversion rates typical of ICE vehicles [12]. Technologies such as regenerative braking and optimized power electronics further enhance their performance and sustainability [15, 16]. Moreover, EV adoption contributes to energy security by diversifying national energy portfolios and reducing reliance on imported petroleum. Market adoption has expanded rapidly. Global EV sales rose from 3.2 million in 2020 to 14 million in 2024, with market share increasing from 4.2% to 18% [17, 18]. One of the strongest drivers of this growth has been the sharp decline in battery pack prices—nearly 90% since 2010—which has enabled mass-market adoption [19]. At the same time, life-cycle assessment studies confirm that EVs consistently outperform internal combustion engine vehicles in terms of greenhouse gas (GHG) emissions, particularly when upstream electricity relies increasingly on renewable sources [20]. Table 1 summarizes key indicators, including sales, market share, battery costs, and charging infrastructure. Figure 1 illustrates the rising trajectory of sales volume and market penetration, while Figure 2 highlights the dual trend of declining battery costs and increasing vehicle range. Figure 1 illustrates the corresponding trajectory, where global EV sales grew more than fourfold between 2020 and 2024. The upward slope of both sales volume and market share highlights the rapid mainstreaming of EVs within the global automobile market, supported by declining battery costs and stronger policy incentives.

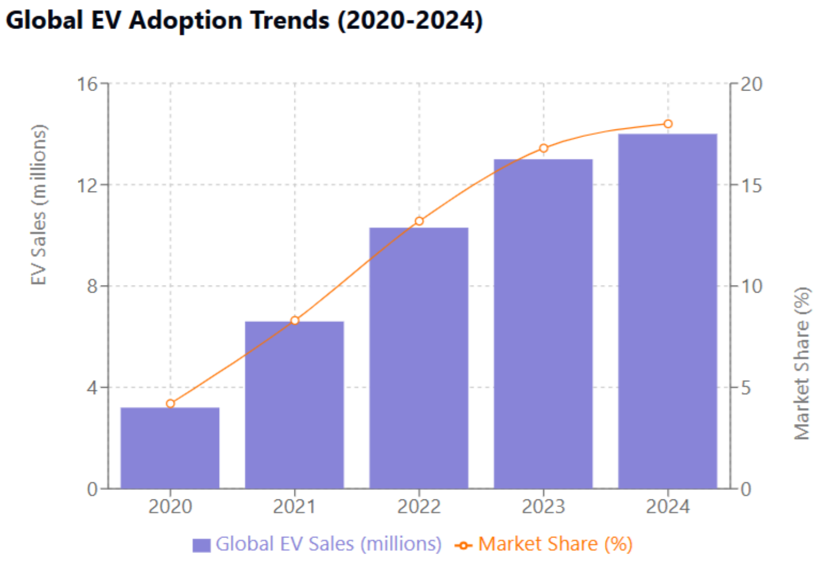

Figure 1: Global EV adoption trends from 2020 to 2024, showing steady growth in both absolute sales and market share. Source: compiled from BloombergNEF (2024) and IEA (2024) [17, 18].

Figure 2 demonstrates the technological progress underpinning adoption, with average battery pack costs falling from 140 to 98 $/kWh between 2020 and 2024, while median EV range increased from 234 to 310 miles. This dual trend highlights the reinforcing cycle of affordability and performance that has accelerated market uptake.

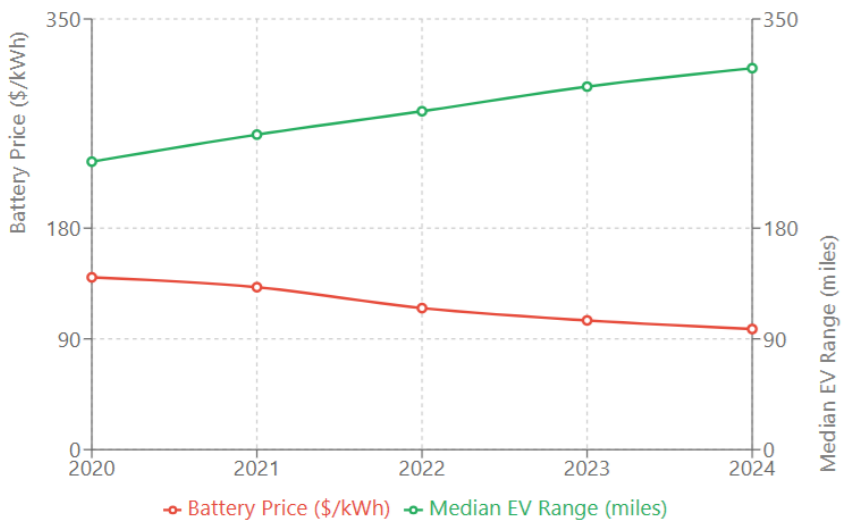

Figure 2: Battery prices and median EV range, 2020–2024. Source: BloombergNEF (2024) and IEA (2024) [17, 18].

The characteristics of charging systems vary considerably across technologies, influencing cost, convenience, and deployment context. Level 1 AC charging is typically confined to residential use due to its low power output and slow speed, while Level 2 AC charging dominates global installations by offering a balance of moderate charging times and feasible installation costs for both residential and public environments. In contrast, DC fast charging provides rapid replenishment but remains a smaller share of deployments given higher capital costs and siting constraints. Table 2 summarizes the key attributes and global deployment shares. As shown in Figure 3, the number of global public charging points more than doubled between 2020 and 2024, paralleling a sharp increase in the number of countries surpassing 10% EV market share. This demonstrates the strong positive feedback between infrastructure provision and adoption, emphasizing that charging availability is one of the most decisive enablers of EV market growth.

Table 2: Charging infrastructure comparison by type. Source: compiled from ICCT (2023), DOE (2024), and industry reports [21, 12].

Charging Type	Power Output	Charging Speed	Installation Cost	Typical Locations	Share of Global Installations
Level 1 (AC)	1.4–1.9 kW	2–5 miles/hour	\$300–\$600	Residential	N/A (primarily private)
Level 2 (AC)	3.3–19.2 kW	10–30 miles/hour	\$2,000–\$10,000	Residential, Workplace, Public	79%
DC Fast Charging	50–350+ kW	3–20 miles/minute	\$20,000–\$150,000	Public, Highway Corridors	21%

3. Policy Frameworks and Incentives

Policy interventions have been instrumental in shaping the trajectory of electric vehicle (EV) adoption worldwide. Governments employ a mix of financial and non-financial incentives to encourage the transition from internal combustion engine vehicles to EVs, while simultaneously investing in the infrastructure required to sustain long-term adoption. Financial instruments include direct purchase subsidies, tax credits, preferential loans, and registration fee reductions, all of which reduce the upfront cost barrier that remains one of the most significant obstacles to widespread EV uptake. Non-financial incentives, such as high-occupancy vehicle (HOV) lane access, preferred parking privileges, exemptions from tolls and congestion charges, and exemptions from low-emission zone restrictions, further enhance consumer willingness to shift toward EV ownership [9, 15]. Beyond consumer-focused incentives, regulatory mechanisms play a critical role in accelerating adoption. Many jurisdictions have implemented zero-emission vehicle (ZEV) mandates that require automakers to gradually increase the share of EVs in their fleets, coupled with increasingly stringent fuel economy and emissions standards. These policies not only drive supply-side transformation but also stimulate research and development in next-generation batteries, charging technologies, and grid integration systems. The cumulative effect has been a global acceleration in EV innovation, supported by both targeted government interventions and private-sector participation [22–24].

The effectiveness of EV policy frameworks varies widely across regions, reflecting differences in institutional capacity, industrial priorities, and social contexts. While some countries emphasize fiscal incentives, others rely on centralized planning or regulatory mandates. The diversity of these approaches highlights that no single strategy is universally applicable, underscoring the importance of policy alignment with local conditions and long-term sustainability goals. Section **??** examines these differences in greater detail through comparative national experiences.

Critics argue that heavy reliance on subsidies is not sustainable in the long run, as fiscal constraints eventually necessitate their phase-out once market maturity is achieved. This raises important questions about the timing and design of transition strategies. Ideally, governments should taper subsidies as EV prices converge with ICE vehicles, while simultaneously strengthening non-financial incentives and regulatory frameworks to maintain momentum. Additionally, equity concerns must be addressed to ensure that benefits are not disproportionately concentrated in urban or affluent regions but are accessible to all segments of society [11]. Integrating EV adoption with broader climate, energy, and social policies, as emphasized by Gudmundsson et al. in their sustainability performance frameworks, offers a pathway to harmonize environmental effectiveness with social inclusivity [9].

4. Case Studies and Comparative Insights

Comparative experiences across countries provide valuable evidence on how different policy mixes, infrastructure strategies, and market dynamics shape electric vehicle (EV) adoption. Norway remains the global leader in EV penetration, where sustained policy support has enabled EVs to surpass 80% of all new car sales in 2024. A consistent package of fiscal and non-fiscal measures—including purchase tax exemptions, road toll waivers, and dense charging deployment—has been key to this transition [25, 18, 17]. The case illustrates how long-term, consistent policy frameworks combined with infrastructure deployment can create a self-reinforcing cycle of adoption, where economies of scale and consumer trust accelerate transition. China represents another instructive example but with a different approach. As the world's largest EV market, China accounted for nearly 60% of global sales in 2024. Centralized planning, industrial strategy integration, and massive infrastructure rollout—including battery swapping stations—have defined its success [26, 27, 22]. Standardization of interfaces, mandatory EV-ready infrastructure in new construction projects, and strong coordination between government agencies and private firms have further accelerated deployment.

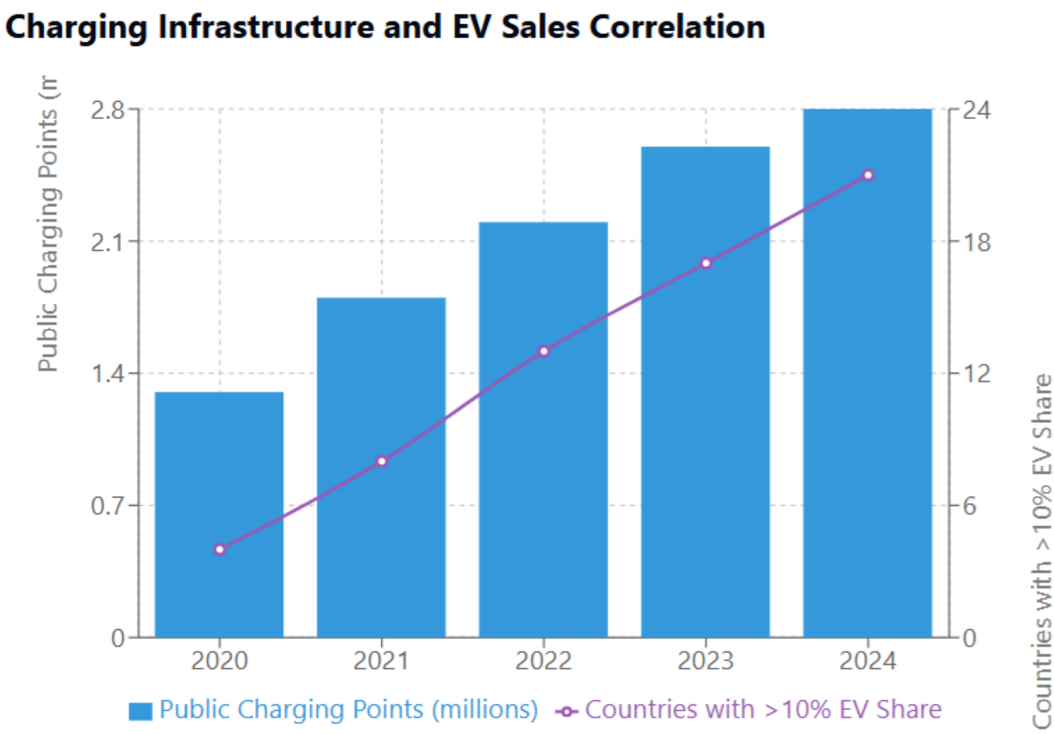

Figure 3: Correlation between growth in public charging infrastructure and EV adoption from 2020 to 2024. As charging points expanded from 1.3 to 2.8 million units worldwide, the number of countries exceeding a 10% EV share increased fivefold. Source: compiled from BloombergNEF (2024) and IEA (2024) [17, 18].

The European Union (EU) and North America, though less advanced in terms of penetration rates compared to Norway and China, present hybrid models where regulatory mandates combine with targeted subsidies. Germany and the Netherlands have pursued aggressive charging deployment alongside tax incentives, while the United States has seen fragmented state-level programs under a weaker federal framework [28, 29, 23]. These cases underscore the importance of policy alignment across scales of governance to avoid fragmented outcomes. The diversity of experiences demonstrates that there is no universal pathway to electrification. Rather, successful strategies are context-dependent, influenced by institutional capacity, market maturity, and socio-economic conditions. Gudmundsson et al. emphasize that performance should be evaluated not only in terms of adoption numbers but also against broader sustainability indicators, including equity of access, integration with renewable energy, and long-term resilience of transport systems [9]. This perspective aligns with the Transportation 5.0 paradigm proposed by Shamsuddoha et al., which argues that future mobility transitions must integrate technology, policy, and inclusivity to create sustainable, people-centered systems [22]. Table 3 highlights cross-national differences in adoption metrics. Norway continues to lead the world with more than 80% of new car sales being electric, supported by dense charging infrastructure and the highest policy strength index. The Netherlands and Sweden also report high penetration rates alongside robust public charging provision. China, despite a lower market share than Norway, accounts for the largest absolute CO_2 reductions due to its market size and rapid infrastructure expansion. By contrast, the United States exhibits relatively low adoption and weaker infrastructure density, illustrating the uneven global progress toward electrification. As illustrated in Figure 4, there is a clear correlation between strong policy environments and high adoption rates. Norway, the Netherlands, and Sweden, which maintain the highest policy strength indices, also exhibit the highest EV market shares. By contrast, countries such as the United States, with relatively modest policy interventions, lag significantly behind despite their large market potential. This underscores the pivotal role of sustained policy commitment in driving large-scale adoption.

5. Challenges and Research Gaps

Despite significant progress in the adoption of electric vehicles (EVs) and supporting infrastructure, multiple challenges persist that constrain the full realization of their sustainability potential. One of the foremost barriers remains affordability. While lifetime costs of EVs are declining due to falling battery prices and efficiency gains, the initial purchase cost continues to be higher than that of conventional internal combustion engine vehicles, particularly in developing markets. This creates equity concerns, as the benefits of electrification risk being concentrated among wealthier urban consumers, while rural and low-income communities face limited access to both vehicles and charging

Table 3: Comparative EV adoption metrics across leading markets in 2024. The Policy Strength Index combines financial incentives, infrastructure investment, and regulatory frameworks into a composite score (0–10). CO_2 reduction values are estimated cumulative impacts. Source: compiled from IEA (2024), BloombergNEF (2024), and national transportation agencies [18, 17].

Country/Region	EV Market Share (%)	Public Chargers per 100 EVs	Public Fast Chargers per 100 km Highway	Policy Strength Index (0–10)	CO_2 Emissions Reduction (MT)
Norway	83	9.2	7.8	9.5	1.8
Netherlands	62	8.3	6.2	8.7	2.3
Sweden	55	7.1	5.5	8.2	2.0
China	39	7.8	5.8	8.8	48.6
Germany	32	6.5	4.2	7.5	7.2
UK	30	5.3	3.8	7.1	5.1
France	28	5.7	3.5	7.3	4.3
US	12	3.2	1.6	6.2	22.4
Global Average	18	5.1	2.8	6.3	108.5

infrastructure [30, 9].

Charging infrastructure itself presents several persistent gaps. Deployment is heavily concentrated in urban centers and along major highways, while rural areas, multi-unit dwellings, and underserved neighborhoods remain inadequately equipped. This uneven distribution exacerbates range anxiety and reinforces patterns of exclusion from clean mobility benefits. Even in regions with substantial infrastructure, reliability challenges such as malfunctioning chargers, incompatible payment systems, and inconsistent standards hinder user confidence [30]. Addressing these gaps requires not only technical solutions but also governance mechanisms that prioritize accessibility and fairness.

The integration of EVs into existing electricity grids is another critical challenge. Without demand management, simultaneous charging can exacerbate peak load demand and necessitate costly grid reinforcements. Duan et al. demonstrate that unmanaged charging in high-adoption regions can diminish the net climate benefit of electrification by increasing reliance on fossil-based peaking power [31]. Smart charging systems, vehicle-to-grid (V2G) technologies, and dynamic pricing strategies offer potential solutions but require large-scale investment and regulatory adaptation. Ensuring compatibility with renewable energy systems is equally important for maximizing environmental gains.

Battery production and recycling raise long-term sustainability questions. The extraction of lithium, cobalt, and nickel has significant ecological and social impacts, including land degradation, water use, and labor concerns in mining regions. Life-cycle assessment studies confirm that while EVs offer reduced operational emissions, upstream production of batteries remains carbon-intensive [13, 14, 29]. Research has emphasized that effective recycling and second-life applications are essential to mitigate these impacts. Studies by Gaines [32] and Neubauer et al. [33] demonstrate the technical and economic feasibility of recycling and repurposing EV batteries for grid storage. Without advances in these areas, EV expansion risks shifting environmental burdens rather than eliminating them.

From a governance perspective, the absence of harmonized international standards for charging connectors, cybersecurity protocols, and grid integration frameworks continues to slow progress. Policy support often remains unstable, with incentives fluctuating in response to fiscal pressures or political shifts, creating uncertainty for industry stakeholders. Equity concerns also remain critical, as access to EVs and charging infrastructure is unevenly distributed across socio-economic groups and regions. Sovacool [34] highlights how poorly designed transitions risk reinforcing social inequalities, while Gudmundsson et al. [9] emphasize that sustainability performance should be evaluated through indicators that capture resilience, equity, and systemic integration. Together, these perspectives underline the importance of coordinated and inclusive governance mechanisms.

Future research should therefore address several pressing areas. First, there is a need for optimized models for siting and scaling charging networks, informed by behavioral data on user charging patterns and regional energy availability. Second, more work is required on circular economy approaches to battery lifecycle management, encompassing sustainable mining, efficient recycling, and integration of secondary-use applications. Third, socio-technical studies should investigate equity in EV adoption, focusing on how infrastructure provision, pricing, and policy can be designed to avoid reinforcing existing inequalities. Finally, systemic research is needed on the interaction between EVs, renewable energy integration, and emerging mobility paradigms such as connected autonomous vehicles, in line with the broader vision of Transportation 5.0 [22]. Together, these areas define the critical frontiers for ensuring that EVs deliver not only technological progress but also comprehensive and inclusive sustainability outcomes.

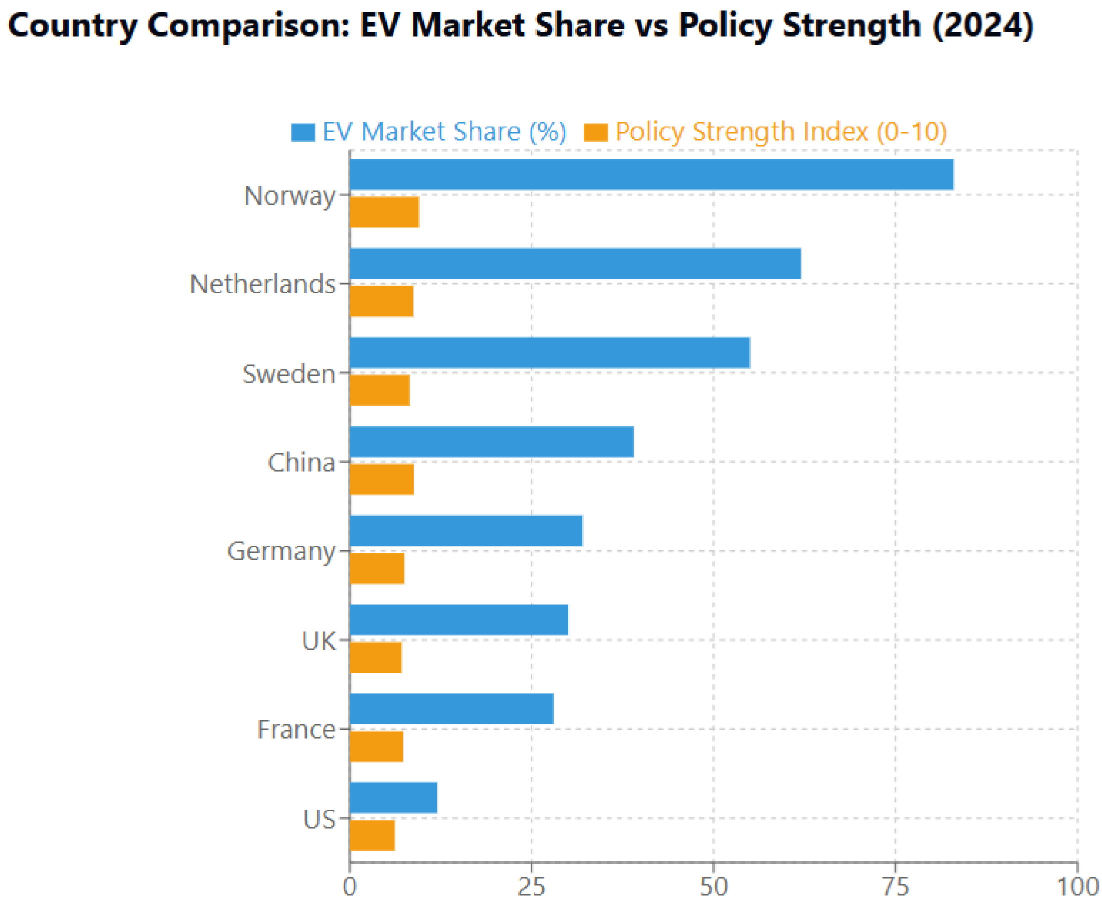

Figure 4: Comparison of EV market share and policy strength index across leading countries in 2024. Strong policy frameworks in Norway, the Netherlands, and Sweden correlate with higher EV penetration, while weaker policy environments in the US and France align with lower adoption levels. Source: compiled from IEA (2024), BloombergNEF (2024), and national transportation agencies [18, 17].

6. Future Directions

Deeper integration with smart grids hinges on bidirectional and scheduled charging. Vehicle-to-grid (V2G) systems, enabled by such technologies, can transform EVs into active components of the energy system, supplying power during peak demand and stabilizing renewable energy fluctuations. Studies show EV fleets can provide capacity and frequency support while generating revenue streams if supported by appropriate tariffs and aggregators [24, 35, 23]. To reduce user friction, emerging infrastructure such as high-power DC charging, wireless inductive charging, and even dynamic in-motion charging corridors should be evaluated for efficiency and cost at scale [36, 37]. Planning models should also co-optimize charger siting with distribution network constraints and renewable energy availability to maximize both grid stability and consumer convenience [38]. Artificial intelligence will coordinate charging, routing, and traffic control across modes. Evidence from connected and automated vehicles indicates substantial energy-saving potential from predictive eco-driving and cooperative signal timing [39]. When paired with shared autonomous fleets, AI can reduce empty miles and right-size supply to demand, complementing mass transit rather than competing with it [40]. Another important future direction concerns material sustainability and circular economy approaches. Research into solid-state batteries, sodium-ion technologies, and sustainable mining practices is advancing rapidly, but equally important is the development of efficient recycling infrastructures. Closed-loop systems that recover lithium, cobalt, and nickel for reuse will be essential to mitigate environmental impacts and resource dependency. Gudmundsson et al. highlight the need to evaluate such transitions against long-term sustainability indicators, ensuring that short-term gains in decarbonization do not result in new systemic vulnerabilities [9]. Equity and accessibility will remain central challenges for the coming decades. Without intentional design, infrastructure and policy frameworks risk deepening inequalities by concentrating benefits in urban or high-income regions. Addressing this requires deliberate strategies to expand rural infrastructure, subsidize access for disadvantaged groups, and integrate EV planning into broader social and economic development goals [30]. By aligning EV adoption with the Sustainable Development Goals, policymakers can ensure that the transition contributes not only to emissions reductions but also to social inclusion and resilience.

Long-term projections from BloombergNEF and the International Energy Agency suggest that EVs may account for 30–40% of global new vehicle sales by 2030, with continued growth thereafter [18, 17]. Yet achieving this trajectory depends on resolving the challenges of affordability, infrastructure deployment, and grid integration. Future research must therefore be multidisciplinary, bridging engineering, economics, environmental science, and social policy to build coherent strategies for scaling EV adoption. In summary, the future of EVs will be defined not only by continued technological progress but also by advances in governance, planning, and integration with emerging mobility systems. Priorities for the coming decade include scaling smart charging and V2G applications, accelerating circular economy approaches to battery materials, and ensuring equity in infrastructure access. Addressing these frontiers will determine whether EV adoption evolves into a genuinely transformative pathway for climate mitigation and sustainable urban mobility.

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Declaration of Competing Interests

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Author Contributions

First Author: Conceptualization, Supervision, Data Analysis, Writing – Review and Editing; **Second Author**: Methodology, Validation, Investigation, Writing – Original Draft; **Third Author**: Software, Visualization, Investigation

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Secure AR-enabled Smart Manufacturing Framework Integrating Machine Learning and Blockchain

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Abstract

Augmented reality (AR) is increasingly adopted in Industry 4.0 to enhance operational efficiency and workplace safety. Yet, most implementations examine productivity and safety in isolation and seldom integrate AR with complementary technologies. This study proposes a secure AR-enabled framework for smart manufacturing that incorporates machine learning for predictive optimization and blockchain for tamper-proof data integrity. The framework is formalized through an algorithmic workflow, a six-layer system architecture, and mathematical models quantifying productivity, safety, economic viability, and user engagement. A simulation-based evaluation with 50 participants across five representative manufacturing tasks indicated measurable improvements: 25% faster task completion, 15% error reduction, 30% downtime reduction, 40% safety improvement, and 35% shorter training duration. While these results provide quantitative evidence of AR's dual role in enhancing efficiency and safety, the findings are limited to controlled simulations and do not fully capture the variability of industrial environments. Future validation in live manufacturing contexts is therefore necessary to establish practical applicability.

Keywords: Augmented Reality; Industry 4.0; Smart Manufacturing; Machine Learning; Blockchain; Safety Management

1. Introduction

Augmented reality (AR) has emerged as a transformative technology in Industry 4.0, enabling operators to access real-time data, contextual instructions, and immersive training directly in the workplace. By overlaying digital content on the physical environment, AR supports faster decision-making and reduces cognitive load, which are critical in complex manufacturing systems where efficiency and safety must be balanced [1]. Despite these advantages, industrial adoption of AR remains limited. Conventional tools such as paper manuals and static displays are inefficient for modern assembly and maintenance tasks, while AR headsets and handheld devices face ergonomic constraints, narrow fields of view, and operator fatigue [2]. Moreover, most implementations evaluate productivity and safety separately, overlooking AR's dual role in enhancing both. Integration of AR with complementary technologies such as digital twins [3], blockchain [4], and IoT-based monitoring [5] has been investigated, but systematic frameworks assessing combined effects on productivity, safety, and economic viability are scarce. Existing works often report qualitative improvements, with few attempts to model and quantify AR's contributions through formal methods and simulation.

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To address these gaps, this study develops a secure AR-enabled smart manufacturing framework that combines machine learning for predictive optimization with blockchain for tamper-proof data integrity. The specific contributions are:

1. Development of mathematical models to quantify AR's impact on productivity, safety, cost–benefit trade-offs, and user engagement.
2. Design of an integrated workflow and layered system architecture unifying AR, machine learning, IoT, and blockchain for secure and optimized operations.
3. Validation of the framework through simulation experiments with representative manufacturing tasks, demonstrating measurable improvements in task performance, error reduction, downtime, training efficiency, and worker safety.

By combining theoretical modeling with simulation-based validation, this study provides quantitative evidence of AR's dual contributions to operational efficiency and workplace safety, reinforcing its role as a foundation for resilient and sustainable Industry 4.0 manufacturing systems.

2. Related Work

Research in augmented reality (AR) for industrial use has largely focused on manufacturing operations and workplace safety, with emerging interest in integrating AR with blockchain, digital twins, and predictive analytics. However, most studies treat productivity and safety as separate concerns and rarely incorporate secure, adaptive architectures validated through formal methods.

In manufacturing, AR has been used to support assembly, maintenance, training, and collaboration. Tang et al. [3] demonstrated improved resource utilization through AR–digital twin integration, while Ren et al. [6] framed AR as an interface to the industrial metaverse. Wang et al. [2] and Fiorentino et al. [7] showed that AR-based assembly guidance reduced operator errors and cognitive load compared to traditional methods. These benefits, though well documented, often rely on case-specific, qualitative insights without generalizable or model-driven evaluation.

Recent works have positioned AR within broader Industry 4.0 ecosystems. McGibney et al. [8] proposed a DLT-based architecture for trusted manufacturing workflows. Egbengwu et al. [9] examined XR applications in distributed collaboration and layout optimization. Despite these developments, empirical validation remains limited to small-scale studies or laboratory simulations. Formal models to quantify performance gains are largely absent.

In safety applications, AR has been employed for hazard identification, compliance training, and ergonomic assessment. Gong et al. [10] surveyed AR-based safety training approaches, and Liu et al. [11] introduced a machine learning-enabled AR system for fall hazard detection. Ardecani et al. [12] studied AR-assisted warnings under workload stress and reported improved decision-making in real-time conditions. While these studies highlight AR's potential to enhance safety, their focus remains on short-term or subjective outcomes rather than measurable safety indices or long-term deployment.

Parallel research in blockchain for manufacturing has addressed data security, traceability, and trust. Santhi and Muthuswamy [13] analyzed blockchain in supply chains, and Romano et al. [14] applied it to certify additive manufacturing provenance. Grünewald et al. [15] offered a taxonomy of blockchain applications in manufacturing. Despite its relevance, blockchain is seldom integrated with AR systems to support real-time, tamper-proof industrial operations.

Existing literature supports AR's promise in productivity and safety enhancement but lacks unified, simulation-backed frameworks that combine AR, machine learning, and blockchain. Studies rarely move beyond descriptive assessments or isolated pilots, and the effects on long-term user performance, ergonomics, and secure operational continuity remain underexplored. The present work addresses these limitations through a comprehensive system architecture that formalizes AR's impact using mathematical modeling and validates performance across representative manufacturing tasks.

3. Methods

This study develops an AR-enabled secure manufacturing framework combining machine learning and blockchain. The design was evaluated through simulation using Unity3D and Vuforia. Figure 1 shows the architecture, where AR modules deliver task guidance and visualization, the machine learning layer monitors operations and builds predictive models, and the blockchain layer encrypts and records validated data on a distributed ledger.

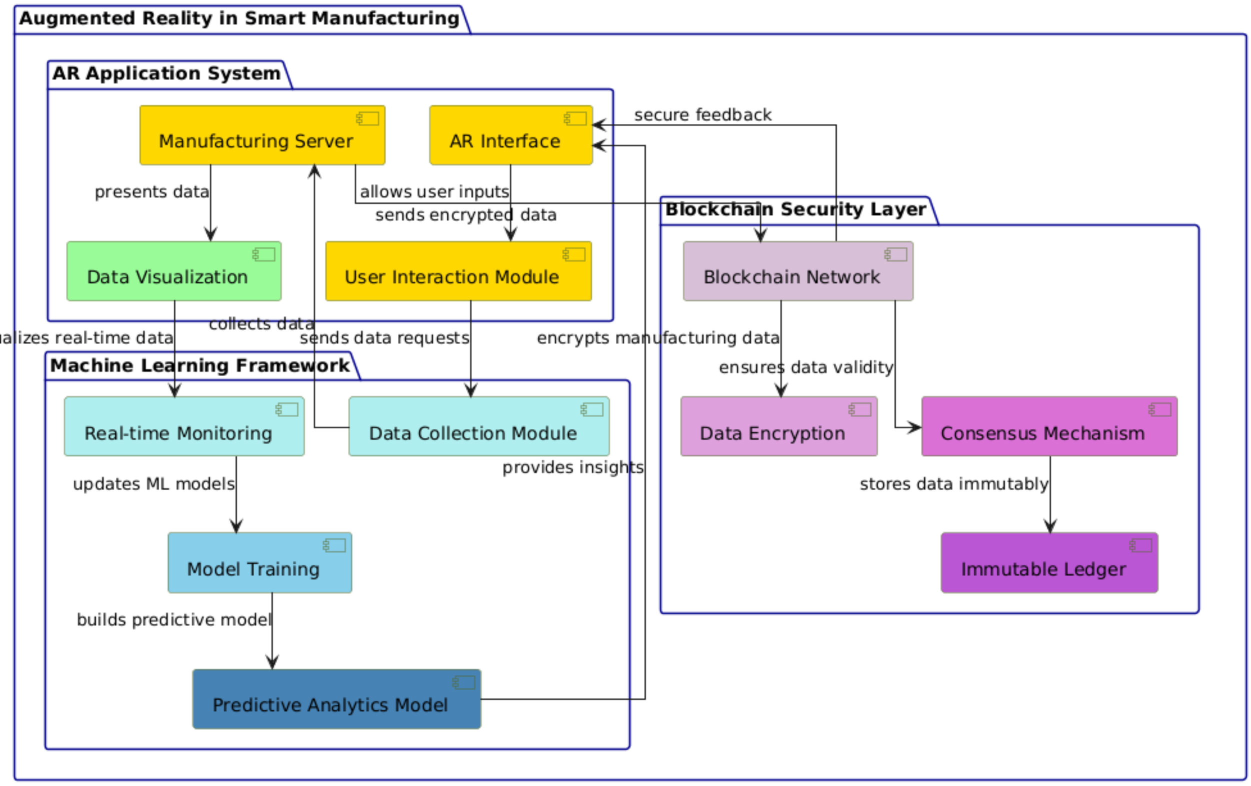

Figure 1: System architecture for AR-enabled secure manufacturing

The workflow begins with data verification and hashing, continues with process execution and monitoring, and concludes with optimized predictions and secure storage. The steps are summarized in Algorithm 1. The reinforcement learning element, conceptually inspired by AlphaZero, was introduced at the design stage but not fully implemented. It is intended for future optimization of task sequences. The simulation was conducted with 50 participants performing representative manufacturing tasks under both manual and AR-assisted conditions. Unity3D generated the virtual factory and task workflows, while Vuforia overlaid AR instructions and hazard cues. Performance was measured through task completion time, error rate, hazard detection, downtime, and training duration. Results are descriptive and reflect simulation outputs rather than statistical inference.

Algorithm 1 AR-Enabled Secure Manufacturing Workflow

Require: Input file F, initial state B
Ensure: Final state E, encrypted output M
1: Verify F and generate hash
2: Initialize B
3: **for** each operation i, j **do**
4: Capture and validate process data
5: Update $B[i][j]$
6: **end for**
7: Predict optimized outcome E using reinforcement learning (conceptual)
8: Encode and encrypt E to obtain M
9: Store M and metadata on blockchain
10: Provide M to AR interface

4. Results

Fifty participants completed five representative manufacturing tasks under baseline and AR-assisted conditions, with three repetitions per task. Primary measures included completion time and error rate, while secondary measures considered downtime, incident rate, and training duration. Simulation parameters are shown in Table 1, and consolidated outcomes in Table 2. Under AR conditions, completion time fell by about 25%, error counts by 15%, downtime by 30%, incident rates by 40%, and training duration by 35%. These gains indicate that AR integration improves both productivity and safety. As these are simulation-derived indicators, they reflect relative improvements rather than statistical inference.

Table 1: Simulation Parameters

Parameter	Value
Participants	50
Equipment simulated	10
Training duration	1 week
Tasks simulated	5
Integration period	2 weeks

Table 2: Observed Outcomes under AR Integration

Metric	Change	Improvement (%)
Completion time	∼20 min faster	25
Error rate	∼5 fewer	15
Downtime	∼2 hrs shorter	30
Incident rate	Reduced	40
Training duration	∼3 days shorter	35

Figures 2 and 3 illustrate the experimental setup and consolidated results. Visualizations highlight the distribution of parameters and relative magnitude of improvement across productivity, safety, downtime, and training.

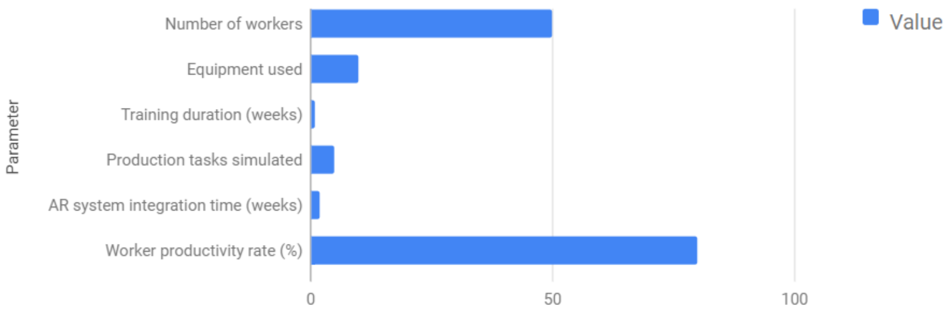

Figure 2: Simulation parameters for AR-enabled manufacturing evaluation.

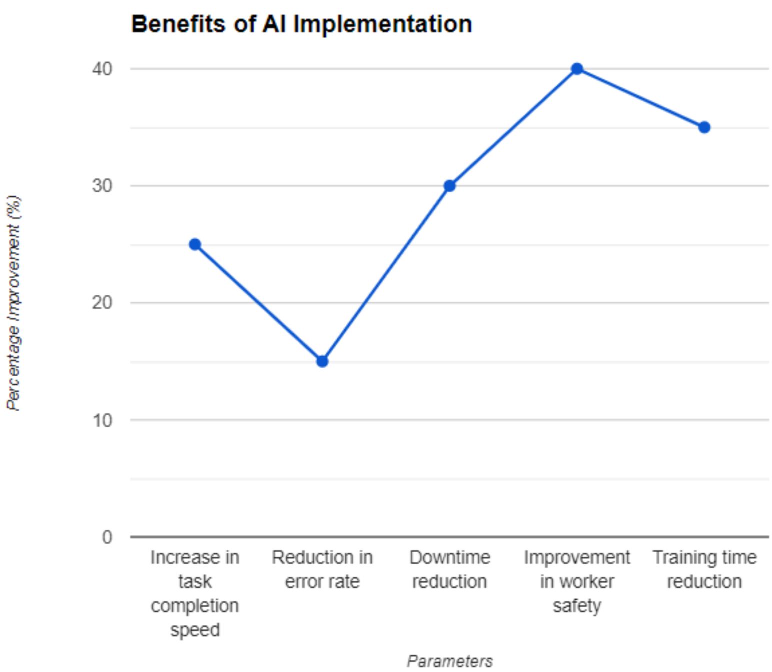

Figure 3: Performance indicators under baseline and AR conditions.

Simulation outcomes align with the conceptual models introduced earlier. Shorter task time and reduced downtime correspond to productivity gains, fewer incidents reflect an improved safety index, lower error rates enhance the cost–benefit ratio, and reduced training duration suggests stronger engagement and faster adaptation. These mappings provide a structured interpretation of the observed improvements.

5. Discussion

The findings show that AR can enhance productivity and safety in manufacturing environments. Faster task completion, fewer errors, shorter downtime, and reduced training duration indicate AR's operational benefits, while lower incident rates underline its preventive value in hazardous settings. These results extend earlier work on AR-assisted assembly and training [16, 17, 2] by offering simulation-based evidence across multiple performance dimensions. A broader implication is that AR serves as a bridge between human operators and automated production systems. Real-time overlays support accurate and timely decision-making, while predictive analytics and blockchain integration ensure secure and transparent operations. This supports Industry 4.0 objectives of efficiency, resilience, and accountability. The study is limited by its reliance on simulated environments, aggregated outcomes, and moderate sample size. Results may not fully capture variability in live shop floors, and ergonomic or long-term adoption aspects were not assessed. Future work should pursue pilot deployments in real factories with longitudinal evaluation of usability, ergonomics, and training durability. Integration with industrial metaverse concepts [6] and adaptive user interfaces may further expand AR adoption and impact.

6. Conclusion

This study proposed a secure framework for augmented reality in Industry 4.0 manufacturing, integrating machine learning for predictive optimization and blockchain for tamper-proof data management. The framework was formalized through an algorithmic workflow, a layered system architecture, and theoretical models of productivity, safety, economic viability, and user engagement. Its feasibility was explored through a controlled simulation involving representative tasks and participants. Simulation outcomes suggested potential improvements, including shorter task completion times, lower error rates, reduced downtime, improved safety indicators, and faster training durations. While these findings highlight AR's promise in simultaneously addressing productivity and safety, they are based on aggregated simulation results rather than statistical analyses of real-world deployments. Accordingly, the contributions of this study should be viewed as conceptual and exploratory. By unifying predictive analytics, secure data exchange, and immersive visualization, the framework illustrates how AR could evolve into a foundational technology for resilient and adaptive smart manufacturing systems. Future work should extend validation to industrial pilot deployments, incorporate longitudinal assessments of ergonomics and workforce acceptance, and explore integration with industrial metaverse platforms to broaden applicability across manufacturing domains.

Declaration of Competing Interests

The authors declare that there are no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Author Contributions

Anamika Singh: Conceptualization, Supervision, Data Analysis, Writing – Review and Editing; **Manisha Pipariya**: Methodology, Validation, Investigation, Writing – Original Draft; **Abhishek Singh**: Software, Visualization, Investigation, Writing – Review and Editing.

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Activation Energy and Dielectric Properties of Epoxy Nanocomposites with Carbon Nanotubes and Carbon Black

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Abstract

This study presents a comparative analysis of multiwall carbon nanotube–epoxy (MWCNT–EP) and carbon black–epoxy (CB–EP) nanocomposites to evaluate the influence of filler concentration and frequency on activation energy and dielectric properties. Activation energy was obtained from the slopes of Arrhenius plots ($\ln\sigma$ vs. $1/T$) at 0.5, 5, and 10 kHz. Both composites showed higher activation energy at 0.5 kHz due to long-range charge-carrier hopping, whereas higher frequencies promoted localized transport between adjacent defect sites. Increasing filler concentration further reduced activation energy, reflecting saturation of dangling bonds, lower density of states, and reduced domain boundary potential. Dielectric analysis revealed that CB–EP composites consistently possessed higher dielectric constants than MWCNT–EP composites at equivalent filler loadings, owing to CB's smaller particle size and greater surface area. For both composites, the dielectric constant decreased with increasing frequency, consistent with interfacial polarization effects. These findings clarify how carbonaceous fillers influence the electrical and dielectric behavior of epoxy nanocomposites.

Keywords: Arrhenius Activation Energy; Dielectric Properties; AC Conductivity; Multiwall Carbon Nanotubes; Carbon Black

1. Introduction

Conducting polymer nanostructures are of great interest because their nanoscale dimensions enable high electrical conductivity, short ionic transport paths, large surface area, low mass, high power-to-weight ratio, and mixed electronic–ionic conduction [1–3]. Advanced dielectric materials are critical for capacitors and pulsed-power devices, where high permittivity, low loss, and reliability are required [4]. In polymer nanocomposites, electrical behavior is strongly governed by filler dispersion, interfacial interactions, filler concentration, curing conditions, and percolation phenomena [5–9]. Below the percolation threshold, these systems behave as insulators, while beyond it conductivity increases through tunneling and hopping mechanisms [10–12]. Carbon-based fillers, including carbon black (CB), carbon nanotubes (CNTs), and carbon fibers, are widely used to enhance polymer conductivity. Among these, CB is particularly effective due to its aggregated morphology, which reduces interparticle distance and increases tunneling contacts, thereby enhancing charge transport [8, 13–19]. CNTs, with high aspect ratio and excellent mechanical strength, also provide substantial reinforcement at low concentrations, though their homogeneous dispersion is challenging because of strong van der Waals interactions [20].

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Electrical transport in CNT–epoxy composites is governed by tube length, alignment, dispersion quality, and curing conditions, and follows a percolation scaling law with a critical concentration and dimensionality-dependent exponent [21, 22]. The temperature dependence of conductivity in polymer nanocomposites typically follows the Arrhenius relation,

$$\sigma = A \exp\left(-\frac{E_a}{k_B T}\right), \tag{1}$$

where A is the pre-exponential factor, E_a the activation energy, k_B Boltzmann's constant, and T absolute temperature [23]. Epoxy-based nanocomposites are particularly attractive because they combine mechanical strength with favorable dielectric response, influenced by space-charge migration, dipolar orientation, and interfacial polarization [5, 24–29]. Although many studies address polymer nanocomposites with carbonaceous fillers, direct comparisons of MWCNT–epoxy (MWCNT–EP) and CB–epoxy (CB–EP) prepared under identical conditions are limited. In particular, the combined influence of filler concentration and frequency on activation energy and dielectric behavior is not yet fully established, despite its importance for optimizing material performance in dielectric and energy-storage applications. The present work addresses this gap by systematically investigating the activation energy, dielectric constant, dissipation factor, and AC conductivity of MWCNT–EP and CB–EP nanocomposites as functions of filler concentration and frequency. The analysis provides insight into the mechanisms by which carbonaceous fillers tailor the electrical and dielectric performance of epoxy-based systems and highlights differences in their effectiveness as reinforcing agents.

2. Materials and Methods

2.1. Materials

Industrial-grade multiwall carbon nanotubes (MWCNTs, 1205YJ, purity >95%) were obtained from Nanostructured & Amorphous Materials, Inc., USA. The nanotubes had an outer diameter of 10–20 nm, inner diameter of 5–10 nm, length of 10–30 μm, specific surface area of 180–230 m^2/g, and bulk density of 0.04–0.05 g/cm^3. Ketjenblack EC-600 JD carbon black (Akzonobel) was used as the second filler, characterized by a BET surface area of 1400 m^2/g, particle diameter of 36 nm, bulk density of 0.12 g/cm^3, iodine absorption of 1000–1100 mg/g, DBP pore volume of 480–510 ml/100 g, and ash content <0.1%. Unmodified epoxy resin (Atul Pvt. Ltd., Valsad, India) served as the polymer matrix, with cured resin density of 1.15 g/cm^3 at room temperature. A standard epoxy-to-hardener ratio of 10:1 was used for all samples.

2.2. Composite Preparation

MWCNT–epoxy (MWCNT–EP) and carbon black–epoxy (CB–EP) composites were prepared by solution casting. For MWCNT–EP, nanotubes were dispersed in epoxy resin preheated to 60 °C and sonicated for 30 min in an ultrasonic bath. The mixture was reheated to reduce viscosity, followed by an additional 30 min of sonication, while minimizing prolonged exposure to prevent nanotube damage. The dispersion was stirred at 200 rpm and 60 °C for 60 min on a hot plate stirrer, cooled to room temperature, and then mixed with hardener to initiate curing. For CB–EP composites, carbon black powder was pre-dried at 60 °C for 30 min to remove moisture. Epoxy resin was heated to 60 °C and mixed with CB to achieve initial dispersion, followed by alternating sonication (30 min), reheating (15 min), and further sonication (30 min). The mixture was stirred at 200 rpm and 50 °C for 60 min, cooled, and then blended with hardener. Vacuum mixing was applied to eliminate entrapped air before casting. Both MWCNT–EP and CB–EP systems were prepared at filler concentrations of 0.5, 1.0, 1.5, 2.0, 2.25, and 2.5 w/v%. The composites were molded into sheets and cured at room temperature for seven days. Square specimens (10 mm × 10 mm × 2 mm) were cut, polished for uniformity, and coated on both sides with conductive silver paint. The solvent was removed by heating the coated samples at 60 °C for 10 min.

2.3. Characterization

Electrical Conductivity and Activation Energy

Electrical conductivity was measured as a function of temperature and frequency. Activation energy was determined using the Arrhenius relation

$$\sigma = A \exp\left(-\frac{E_a}{k_B T}\right), \tag{2}$$

where σ is conductivity, A the pre-exponential factor, E_a the activation energy, k_B Boltzmann's constant, and T absolute temperature. Values of E_a were obtained from the slopes of Arrhenius plots of $\ln \sigma$ versus $1/T$ at different frequencies.

Dielectric Properties

Dielectric measurements were carried out using a Wayne Kerr 6500B impedance analyzer in the frequency range of 500 Hz to 10 kHz. A Wayne Kerr TF-1000 solid sample holder and a high-temperature furnace were employed, with RS-232 and GPIB interfaces enabling computer control. The real (ε') and imaginary (ε'') parts of permittivity were recorded as functions of frequency and temperature. The dielectric constant (ε') was analyzed to assess charge transport and interfacial polarization.

AC Conductivity and Dissipation Factor

AC conductivity (σ_{ac}) was derived from dielectric measurements using the relation

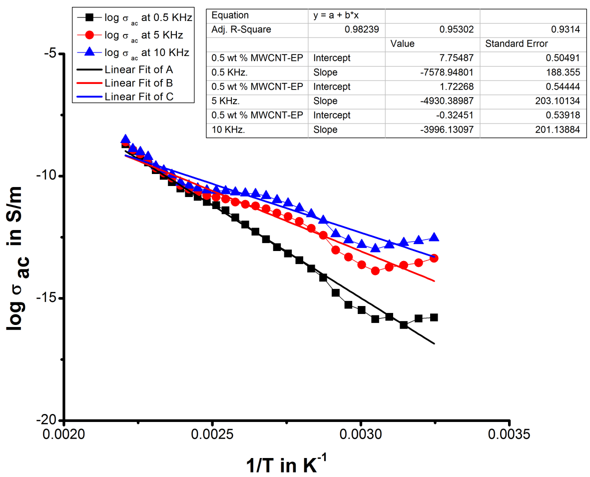
$$\sigma_{ac} = \varepsilon_0 \varepsilon'' \omega,$$

where ε_0 is the permittivity of free space, ε'' the imaginary permittivity, and ω the angular frequency. The dielectric dissipation factor ($\tan\delta$), representing energy loss in the composites, was calculated as the ratio of ε'' to ε'.

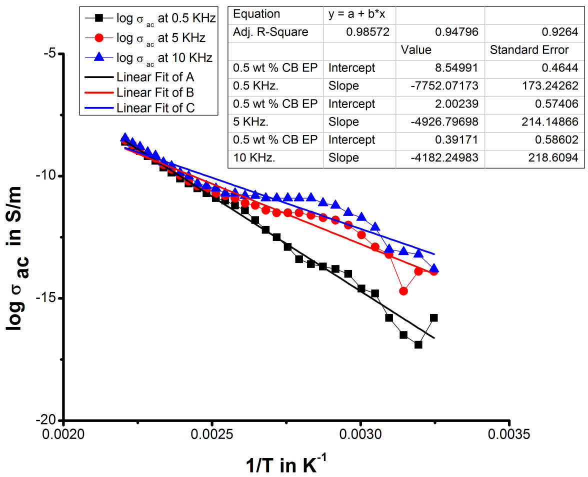
3. Results and Discussion

3.1. Activation Energy

Figure 1 shows Arrhenius plots of $\ln(\sigma)$ versus $1/T$ for 0.5 w/v% (a) MWCNT–EP and (b) CB–EP composites at 0.5, 5, and 10 kHz. Activation energies calculated from the slopes are summarized in Tables 1–3. In both composites, E_a decreased with increasing frequency, being highest at 0.5 kHz and lowest at 10 kHz. This trend indicates a transition from phonon-assisted hopping at low frequencies to localized transport between nearest-neighbor defect sites at higher frequencies.



(a) MWCNT–EP composites.



(b) CB–EP composites.

Figure 1: Arrhenius plot of $\ln(\sigma)$ versus $1/T$ for 0.5 w/v% (a) MWCNT–EP and (b) CB–EP composites at 0.5, 5, and 10 kHz.

Table 1: Activation energy (E_a) of MWCNT–EP and CB–EP composites at 0.5 kHz.

Filler (w/v%)	MWCNT–EP (eV)	CB–EP (eV)
0.0	0.6495	0.6495
0.5	0.6530	0.6679
1.0	0.7170	0.6868
1.5	0.6834	0.6727
2.0	0.6548	0.6888
2.5	0.7004	0.5653

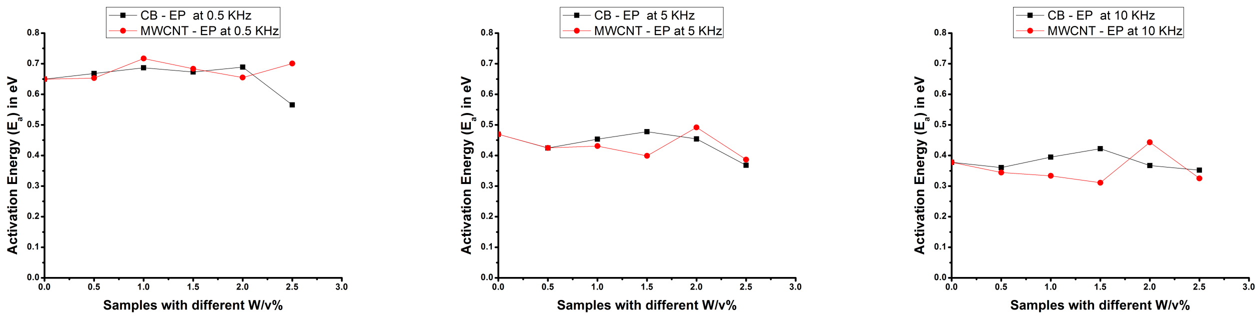
Table 2: Activation energy (E_a) of MWCNT–EP and CB–EP composites at 5 kHz.

Filler (w/v%)	MWCNT–EP (eV)	CB–EP (eV)
0.0	0.4693	0.4693
0.5	0.4248	0.4245
1.0	0.4308	0.4534
1.5	0.3987	0.4778
2.0	0.4920	0.4541
2.5	0.3864	0.3680

Table 3: Activation energy (E_a) of MWCNT–EP and CB–EP composites at 10 kHz.

Filler (w/v%)	MWCNT–EP (eV)	CB–EP (eV)
0.0	0.3776	0.3776
0.5	0.3443	0.3603
1.0	0.3335	0.3944
1.5	0.3109	0.4221
2.0	0.4430	0.3672
2.5	0.3252	0.3520

Figure 2 illustrates the effect of filler concentration on activation energy (E_a) at different frequencies. In MWCNT–EP composites, E_a increased slightly with loading at 0.5 kHz [Figure 2(a)] but decreased with loading at higher frequencies [Figures 2(b) and 2(c)]. CB–EP composites, in contrast, showed a consistent decrease in E_a with increasing filler concentration at all frequencies. The lower activation energies in CB–EP systems are attributed to smaller particle size and larger surface area of CB, which enhance dispersion and tunneling efficiency. In MWCNT–EP composites, agglomeration at higher concentrations hinders uniform dispersion and elevates E_a, especially at low frequencies.

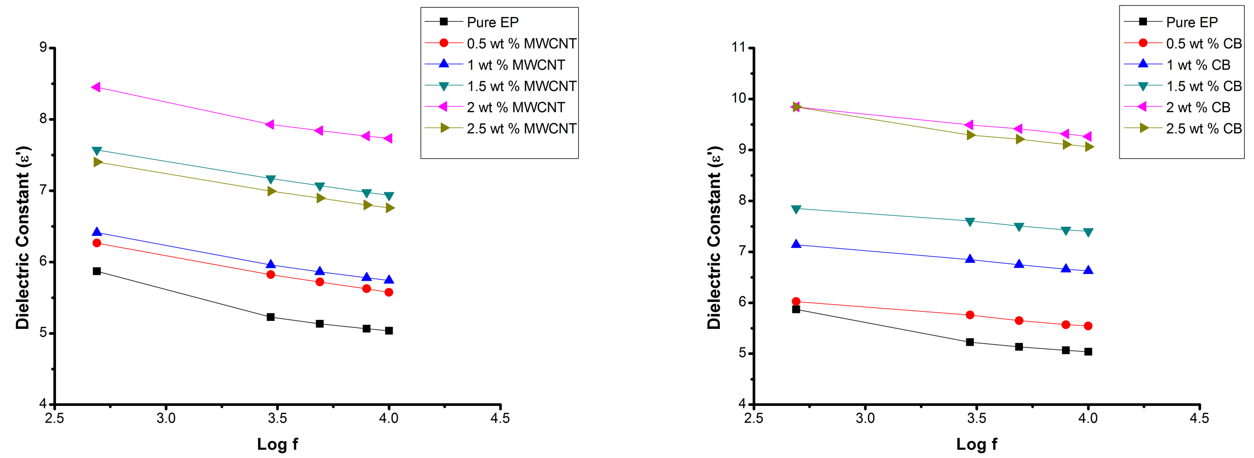


(a) 0.5 kHz **(b)** 5 kHz **(c)** 10 kHz

Figure 2: Effect of filler concentration on activation energy (E_a) in (a) 0.5 kHz, (b) 5 kHz, and (c) 10 kHz.

3.2. Dielectric Constant (ε')

Figure 3 shows the variation of dielectric constant with frequency and filler concentration for both MWCNT–EP and CB–EP composites. In both systems, ε' decreased with increasing frequency from 0.5 to 10 kHz due to the inability of dipoles and interfacial charges to follow the rapid field oscillations. At low frequencies, interfacial polarization dominates because of charge accumulation at filler–matrix boundaries. In MWCNT–EP composites [Figure 3(a)], ε' increased with filler loading, rising from 6.266 to 8.453 at 0.5 kHz and from 5.574 to 7.734 at 10 kHz as concentration increased from 0.5 to 2 w/v%. The improvement is attributed to the high aspect ratio of MWCNTs, which facilitates network formation. In CB–EP composites [Figure 3(b)], dielectric constants were consistently higher, increasing from 6.023 to 9.844 at 0.5 kHz and from 5.546 to 9.266 at 10 kHz. The finer particle size and larger surface area of CB produce stronger Maxwell–Wagner–Sillars polarization, explaining the superior dielectric performance.

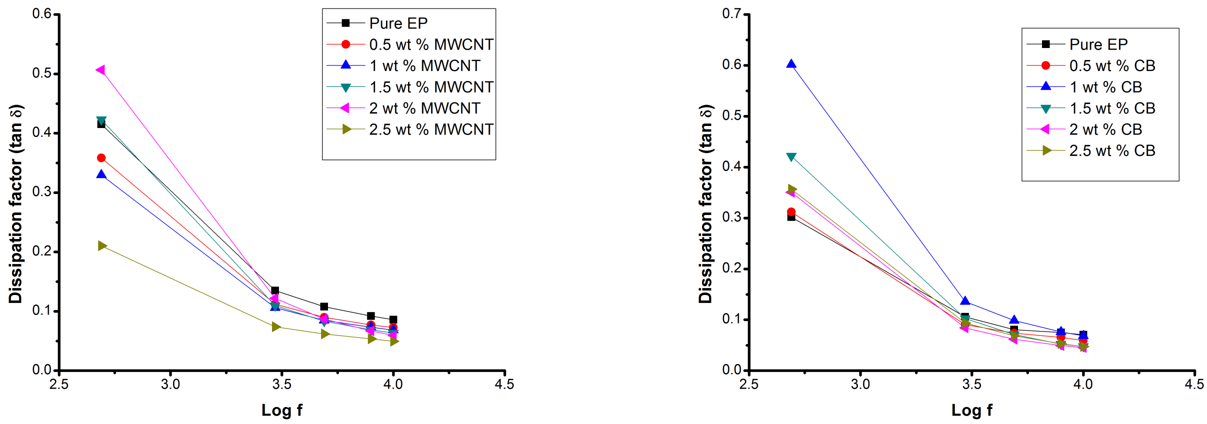


(a) MWCNT–EP composites at different filler concentrations. **(b)** CB–EP composites at different filler concentrations.

Figure 3: Variation of dielectric constant (ε') with $\log f$ for (a) MWCNT–EP and (b) CB–EP composites.

3.3. Dielectric Dissipation Factor (tan δ)

Figure 4 shows the variation of dielectric dissipation factor (tan δ) with frequency for (a) MWCNT–EP and (b) CB–EP composites at different filler concentrations. In both composites, tan δ decreased with increasing frequency but increased with filler loading. For MWCNT–EP composites [Figure 4(a)], values rose from 0.358 at 0.5 w/v% to 0.506 at 2 w/v% (0.5 kHz). For CB–EP composites [Figure 4(b)], the increase was smaller, from 0.312 to 0.350 over the same range. The rise in tan δ with concentration is attributed to enhanced interfacial polarization and charge-carrier density, while aggregation at high loadings reduces homogeneity and moderates loss growth.

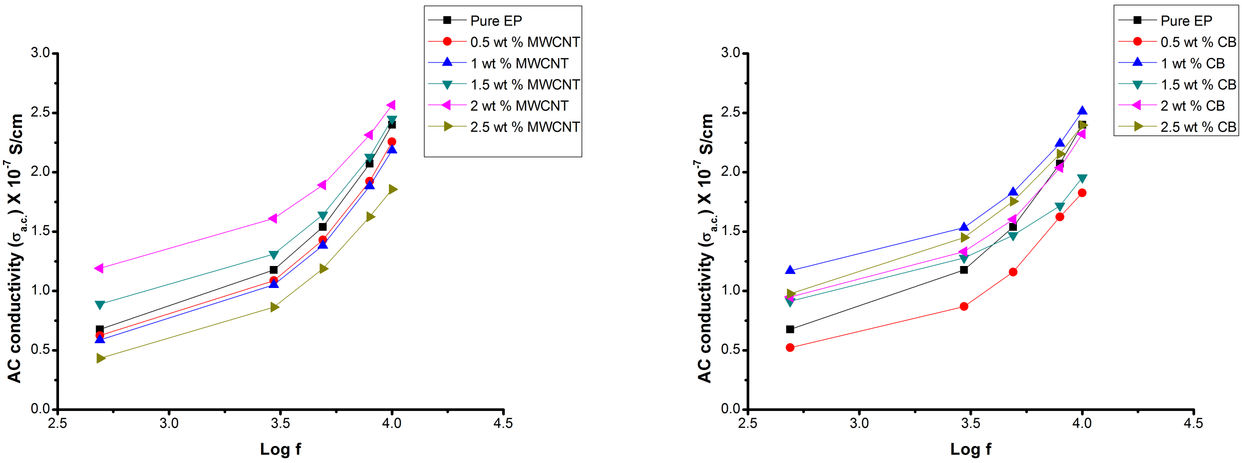


(a) MWCNT–EP composites. **(b)** CB–EP composites.

Figure 4: Variation of dielectric dissipation factor (tan δ) with $\log f$ for (a) MWCNT–EP and (b) CB–EP composites at different filler concentrations.

3.4. AC Conductivity (σ_{ac})

Figure 5 illustrates the frequency dependence of AC conductivity for (a) MWCNT–EP and (b) CB–EP composites at different filler concentrations. In both systems, σ_{ac} increased with filler concentration and frequency, consistent with improved charge transport. For MWCNT–EP composites [Figure 5(a)], conductivity rose sharply beyond 3 kHz, signifying the development of percolated conductive networks. At low concentrations, incomplete networks restricted conduction, while higher loadings enabled continuous pathways. Very high concentrations, however, promoted agglomeration, which disrupted network uniformity. For CB–EP composites [Figure 5(b)], conductivity improved steadily with concentration and frequency. At low filler levels, transport occurred mainly by electron hopping between localized sites, while at higher loadings percolation dominated. The frequency dependence followed a power-law trend, reflecting phonon-assisted hopping and interfacial polarization. These results align with the dielectric response and confirm that filler type and concentration strongly influence transport mechanisms in epoxy nanocomposites.



(a) MWCNT–EP composites.

(b) CB–EP composites.

Figure 5: Variation of AC conductivity (σ_{ac}) with $\log f$ for (a) MWCNT–EP and (b) CB–EP composites at different filler concentrations.

4. Conclusions

A comparative analysis of multiwall carbon nanotube–epoxy (MWCNT–EP) and carbon black–epoxy (CB–EP) composites was conducted to evaluate the effect of filler concentration and frequency on Arrhenius activation energy and dielectric properties. The activation energy of both composites was higher at 0.5 kHz than at 5 or 10 kHz. At 0.5 kHz, CB–EP composites exhibited lower activation energies than MWCNT–EP composites, attributed to the smaller particle size and larger surface area of CB, which facilitate charge transport. The dielectric constant at a given frequency was inversely related to activation energy, reflecting the influence of relaxation dynamics. CB–EP composites consistently showed higher dielectric constants than MWCNT–EP composites across all filler concentrations and frequencies, confirming superior interfacial polarization due to finer dispersion. Overall, filler concentration and frequency influence activation energy and dielectric constant primarily through filler type, polymer compatibility, and dispersion quality. These results highlight the importance of optimizing filler selection and loading for tailoring polymer nanocomposites toward specific dielectric applications.

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Declaration of Competing Interests

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Author Contributions

Manindra Trihotri: Conceptualization, Methodology, Experimental Investigation, Data Curation, Formal Analysis, Writing – Original Draft, Writing – Review and Editing, Supervision; **U. K. Dwivedi**: Validation, Resources, Data Interpretation, Visualization, Writing – Review and Editing.

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