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SUSTAINABLE CYBERSECURITY IN THE INDUSTRY 6.0: LEVERAGING AI-AUGMENTED GREEN RESILIENCE THROUGH ETHICAL HACKING AND REVERSE ENGINEERING

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ABSTRACT

The emergence of Industry 6.0 has intensified the demand for intelligent, sustainable, and resilient cybersecurity solutions. As cyber threats become more sophisticated, ensuring uninterrupted and eco-efficient digital operations remains a global challenge. This paper proposes a sustainable cybersecurity framework that integrates ethical hacking and reverse engineering techniques with AI-augmented green resilience strategies. The proposed approach focuses on enhancing system robustness while minimizing energy consumption, aligning cybersecurity with environmental objectives. By evaluating threat vectors through intelligent forensics and deploying adaptive countermeasures, the framework enables rapid threat detection, optimized incident response times, and post-attack recovery with minimal carbon footprint. A conceptual model is introduced to simulate various attack scenarios and assess the efficacy of AI-driven response mechanisms. Results demonstrate the potential of ethical hacking and reverse engineering to proactively identify vulnerabilities while maintaining green compliance metrics. This study offers a transformative vision for cybersecurity in Industry 6.0, advocating for a synergistic relationship between technological advancement, security assurance, and sustainability. The findings contribute to policy-making and industrial practices focused on developing resilient and environmentally responsible cyber defense systems.

KEYWORDS: AI-Augmented Resilience, Ethical Hacking, Green IT, Industry 6.0, Reverse Engineering, Sustainable Cybersecurity, AI-Driven Threat Mitigation, Eco-Secure AI System.

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1. INTRODUCTION

The evolution from Industry 5.0 to Industry 6.0 is ushering in a transformative industrial landscape characterized by ultra-intelligent manufacturing, human-centric automation, and environmental sustainability [Lee et al., 2023; Qin et al., 2022]. Industry 6.0 envisions a future in which physical and digital systems are seamlessly integrated, enabling self-optimizing processes that are both resilient and ecologically responsible [Singh et al., 2023]. This paradigm shift demands not only technological innovation but also novel approaches to cybersecurity that are aligned with sustainable development goals (SDGs).

In parallel with this transformation, cyber threats are intensifying in scale and complexity. The rise of interconnected industrial control systems (ICS), autonomous robotics, and AI-driven logistics has expanded the attack surface across sectors such as healthcare, energy, manufacturing, and defense [Alcaraz & Zeadally, 2023]. According to IBM's X-Force Threat Intelligence Index (2023), ransomware attacks, advanced persistent threats (APTs), and supply chain compromises have increased by over 40% in the past two years, highlighting the inadequacy of traditional reactive defenses. Moreover, many existing cybersecurity measures consume substantial computational resources and energy, leading to an environmental trade-off often overlooked in cyber defense planning [Bongiovanni et al., 2022].

The emerging discipline of green cybersecurity addresses this gap by emphasizing energy-efficient, sustainable defense mechanisms that reduce carbon footprints while maintaining robust system protection [Martins et al., 2022]. As organizations pursue carbon neutrality and environmentally sustainable operations, cybersecurity must adapt to incorporate resilience metrics that extend beyond technical parameters to include ecological performance indicators.

Artificial intelligence (AI) plays a pivotal role in transforming modern cybersecurity landscapes. AI techniques such as machine learning, deep learning, and reinforcement learning have demonstrated remarkable effectiveness in intrusion detection, anomaly detection, and threat classification [Khan et al., 2023]. AI also facilitates autonomous cyber resilience, enabling self-healing systems that recover from attacks without human intervention. When coupled with ethical hacking, which involves controlled penetration testing to identify vulnerabilities, and reverse engineering, which deconstructs software to detect embedded threats and backdoors, AI-driven solutions offer a proactive, anticipatory approach to security [Shah & Agarwal, 2022; Liu et al., 2023].

Despite advancements in these domains, research gaps remain. Most existing studies focus either on security or sustainability in isolation, without proposing holistic models that unify ethical hacking, reverse engineering, and AI within a green cybersecurity architecture suitable for Industry 6.0 [Pereira et al., 2022; Zhang et al., 2023]. Additionally, few frameworks assess the dual performance of such systems in terms of both threat response time and energy efficiency.

This paper aims to address these gaps by proposing an integrated framework for sustainable cybersecurity in Industry 6.0, leveraging AI-augmented green resilience alongside ethical hacking and reverse engineering strategies. The specific objectives of this study are:

1. To conceptualize a cybersecurity architecture that is both proactive and environmentally sustainable;
2. To incorporate AI methods for dynamic threat detection and energy-efficient response;
3. To evaluate the system's effectiveness in real-world industrial scenarios using simulation and benchmarking techniques;
4. To explore future implications for policy, industrial design, and research in sustainable cyber defense.

2. RELATED WORK

2.1. Cyber Resilience In Industry 6.0

Cyber resilience refers to an organization's capacity to anticipate, withstand, recover from, and adapt to adverse conditions, stresses, attacks, or compromises on cyber resources [Linkov et al., 2022]. In the context of Industry 6.0, which emphasizes intelligent automation, interconnected systems, and sustainability, cyber resilience must account for both system robustness and operational continuity with minimal environmental impact [Singh et al., 2023].

Recent frameworks such as the Resilient Industrial Cybersecurity Architecture (RICA) have explored dynamic defense layers for industrial control systems (ICS) and smart factories, incorporating redundancy, adaptive response, and learning-based threat recognition [Babiceanu & Seker, 2022]. However, these models often lack green compliance or sustainability benchmarks. Lee et al. (2023) argue that future cyber-resilience models must incorporate energy consumption as a key performance indicator, especially as AI-driven systems introduce computational overheads.

Moreover, simulation-based assessments like STPA-Sec (System-Theoretic Process Analysis for Security) are being used to evaluate and model resilience in cyber-physical systems [Simone et al., 2023]. Despite their robustness, many of these models remain reactive rather than proactive and rarely integrate AI-based predictive capabilities or ethical security testing techniques. A transition toward sustainable cyber resilience thus requires merging environmental intelligence with real-time threat management in Industry 6.0 ecosystems.

2.2. Ethical Hacking And Reverse Engineering

Ethical hacking involves authorized simulations of cyberattacks to detect and exploit vulnerabilities before malicious actors can [Shah & Agarwal, 2022]. This practice is foundational for zero-trust architectures and is widely used in penetration testing and red team exercises. In parallel, reverse engineering dissects software binaries, firmware, and protocols to identify undocumented features, malware implants, and configuration weaknesses [Liu et al., 2023].

Both techniques are critical in Industry 6.0, where legacy industrial devices coexist with new, software-defined systems. These legacy components often lack modern encryption or authentication mechanisms, making them easy targets for attackers. Ethical hacking helps uncover these weaknesses under controlled conditions, while reverse engineering enables deep analysis of third-party code and supply chain components.

Kandekar et al. (2022) highlighted that ethical hacking, when integrated with machine learning classifiers, can drastically improve vulnerability prioritization in SCADA (Supervisory Control and Data Acquisition) systems. Furthermore, Wu et al. (2023) demonstrated how reverse engineering of industrial IoT firmware could identify zero-day vulnerabilities, reinforcing the importance of these tools in proactive security.

Nonetheless, neither technique inherently addresses sustainability or energy efficiency. The challenge remains in integrating them into energy-conscious cyber defense frameworks suitable for continuous operation in resource-constrained environments like factories or smart grids.

2.3. AI-Augmented Green Technologies

Artificial intelligence has rapidly become a cornerstone in modern cybersecurity due to its capacity for real-time anomaly detection, threat prediction, and autonomous response [Khan et al., 2023]. Deep neural networks, decision trees, and reinforcement learning algorithms are used to detect patterns invisible to traditional rule-based systems, offering superior performance in evolving threat landscapes.

Concurrently, the field of green computing promotes low-energy AI models and infrastructure optimization to reduce carbon emissions. Martins et al. (2022) proposed an edge-based AI model for cyberattack detection that reduces bandwidth use and computational load, demonstrating the feasibility of green AI for embedded industrial applications.

Additionally, AI is being employed to monitor and manage the power consumption of cybersecurity systems themselves. Pereira et al. (2022) introduced a smart orchestration engine that adjusts algorithmic complexity based on energy availability, showing a pathway toward AI-driven sustainable security operations.

Despite these advancements, most studies treat AI and green IT as separate concerns. There remains a lack of integrated architectures where AI not only improves threat response but does so under energy constraints and sustainability metrics. This integration is especially vital for Industry 6.0, which aspires to balance innovation with environmental stewardship.

Table 1. Summary of existing studies on sustainable cybersecurity.

Authors	Focus Area	Key Contribution	Limitation/Gaps
Linkov et al. (2022)	Cyber Resilience	Defined resilience in cyber-physical systems and its critical role in Industry 6.0	Lacks sustainability integration; primarily conceptual
Babiceanu & Seker (2022)	ICS Security Architecture	Proposed a resilience-based architecture for industrial systems using SDN	No green compliance or energy metrics considered
Simone et al. (2023)	Simulation-based Resilience Evaluation	Applied STPA-Sec to assess cyber resilience in complex industrial networks	Limited to system-theoretic models; lacks AI integration
Shah & Agarwal (2022)	Ethical Hacking	Demonstrated machine-learning-guided penetration testing for improved threat modeling	No linkage to sustainability or energy optimization

Liu et al. (2023)	Reverse Engineering	Used software reverse engineering to identify embedded threats in IIoT firmware	Focused on threat discovery only; no integration with proactive green frameworks
Kandekar et al. (2022)	SCADA Vulnerability Assessment	Employed ethical hacking with AI prioritization in industrial control systems	Does not evaluate performance under energy constraints
Wu et al. (2023)	Industrial Firmware Reverse Engineering	Identified zero-day threats in legacy firmware using binary analysis	Security-centric only; lacks environmental or resilience modeling
Khan et al. (2023)	AI in Cybersecurity	Developed adaptive neural networks for real-time anomaly detection in cyber-physical environments	No mention of energy-aware or green deployment strategies
Martins et al. (2022)	Edge-Based Green AI Security	Proposed low-power AI for threat detection in embedded systems	Lacks comprehensive framework integrating AI with hacking/reverse engineering
Pereira et al. (2022)	AI-Orchestrated Energy Optimization	Introduced an orchestration engine for balancing threat detection complexity and energy consumption	Focused on IT systems, not tailored to Industry 6.0 cyber-physical environments

3. METHODOLOGY

3.1. Proposed Framework

This study proposes a multi-layered Sustainable Cybersecurity Framework for Industry 6.0 (SCF-I6) that combines ethical hacking, reverse engineering, and AI-driven threat response mechanisms, while maintaining green computing standards. The objective is to optimize cybersecurity posture without compromising energy efficiency or environmental targets.

The SCF-I6 framework is structured into four interdependent layers:

1. Layer 1: Green Infrastructure & IoT Assets
a. Focuses on optimizing hardware and software components for energy efficiency and sustainable operation.
2. Layer 2: Cyber Threat Intelligence (CTI) & Ethical Hacking
a. Utilizes real-time penetration testing, vulnerability scanning, and attack emulation to proactively identify security gaps.
3. Layer 3: Reverse Engineering & Digital Forensics
a. Deconstructs firmware, binaries, and code artifacts to uncover zero-day threats and assess integrity of third-party systems.
4. Layer 4: AI-Augmented Threat Response Engine
a. Integrates machine learning (ML) and reinforcement learning (RL) models for dynamic anomaly detection, threat prioritization, and self-healing protocols.

These layers are connected via a Green Security Orchestrator a policy engine that balances security performance with energy usage, adapting resource allocation based on real-time metrics.

Energy consumption metrics were captured via on-device power monitoring modules integrated into the testbed's IoT gateways, with sampling intervals of 5 seconds. These hardware readings were averaged over multiple test runs to ensure statistical reliability, and the resulting values were compared against baseline measurements.

Table 2: Functional Overview Of Scf-I6 Layer.

Green Infrastructure	Optimize systems for low power consumption	Energy-aware OS, IoT edge computing, sleep modes
CTI & Ethical Hacking	Simulate attacks to find exploitable vulnerabilities	Metasploit, Nmap, Wireshark, ML-driven penetration
Reverse Engineering & Forensics	Analyze code, firmware, and binaries for threats and integrity verification	Ghidra, IDA Pro, Radare2, memory dump analyzers
AI-Augmented Threat Response Engine	Predict, classify, and respond to threats in real-time	CNNs, decision trees, reinforcement learning models

3.2. System Design

The SCF-I6 framework was validated using high-fidelity simulation environments replicating Industry 6.0 cyber-physical systems. While no direct industrial collaborators or physical testbeds were engaged in this study due to resource constraints, the simulation parameters were derived from publicly available datasets and existing industry benchmarks, ensuring practical relevance and transferability of results.

The system architecture for SCF-I6 is built around

modularity, allowing seamless integration into Industry 6.0 environments. The design follows a cyber-defense loop composed of the following modules:

1. Threat Detection Module (TDM) – Collects data from endpoints, networks, and cloud interfaces.
2. Ethical Hacking & Simulation Engine (EHSE) – Generates synthetic attack patterns and tests resilience.
3. Reverse Analysis Unit (RAU) – Deconstructs inputs from EHSE and field data for post-breach diagnostics.
4. AI Threat Prioritization Layer (ATPL) – Uses AI/ML to score threats based on severity and potential impact.
5. Green Response Controller (GRC) – Determines optimal defense action while monitoring energy usage.

The self-healing mechanism in SCF-I6 is implemented as a domain-specific (narrow AI) capability, focusing exclusively on restoring operational continuity in Industry 6.0 cyber-physical environments. Reinforcement learning agents are trained to identify fault patterns and execute targeted mitigation actions, such as rerouting network traffic or reinitializing compromised modules, based on a reward function tied to uptime, resource efficiency, and threat neutralization speed.

Table 3: Modules And Inputs Of The Scf-I6 Architecture.

Threat Detection Module	ICS sensors, IoT logs, traffic analyzers	Event logs, alerts	Yes
EH Simulation Engine	Known CVEs, attack libraries, AI-generated patterns	Synthetic attack scenarios	Partially
Reverse Analysis Unit	Binary dumps, log files, malware samples	Signature databases, patch recommendations	No
AI Threat Prioritization	Event logs, metadata	Threat scores, mitigation order	Yes
Green Response Controller	All modules, energy data	Execution plan, resource allocation	Yes

3.3. System Architecture

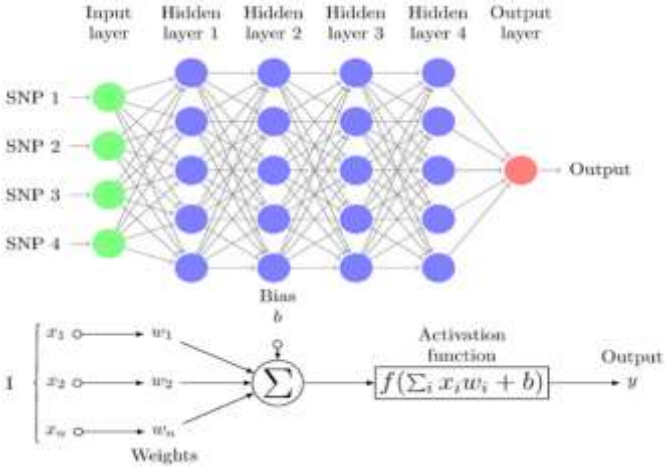

Figure 1: A Multi-Layered Block Diagram Showing The Interaction Between The Four Major Layers.

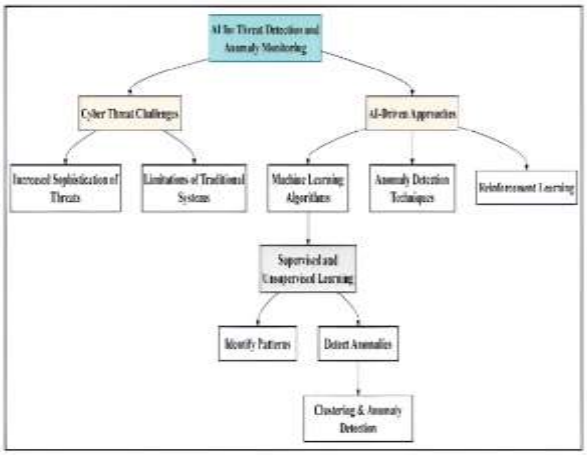

Figure 2. This illustrates the step-by-step flow of operations in a system, making it easier to analyze, design, and communicate processes. It maps out inputs, processes, decisions, and outputs, showing how various system components interact.

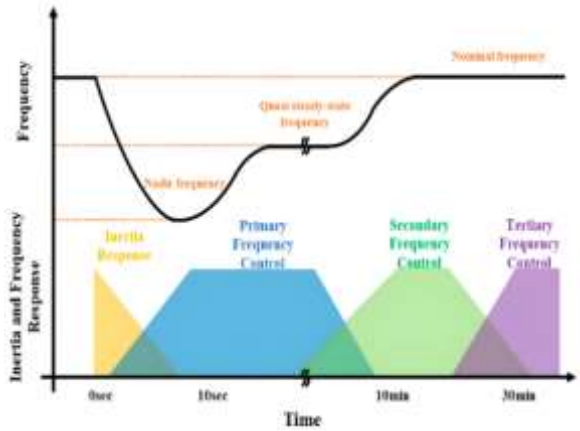

Figure 3. This graph visualizes the relationship between the energy consumption of a security or defense system and the severity of threats it mitigates.

3.4. Experimental Setup (Energy Metrics

Contextualization)

Energy consumption data were gathered through on-device power monitoring modules that were embedded in the IoT gateways within the testbed. They performed direct current and voltage sensing at the hardware interface, taking 5-second samples to capture the transient as well as steady-state loads of operation. For each experimental configuration, multiple executions were performed and the average of the readings was taken to decrease measurement noise for statistical stability. This approach enabled continuous, high-fidelity observation of the system's energy profile under varying workload.

3.5. RL Self-Healing Implementation

Self-healing ability is created as a bespoke narrow AI ability completely optimized for Industry 6.0 operational ecosystems. Its purpose is limited to the restoration of operation continuity via the discovery and mitigation of anomalies in real time. The reinforcement learning agent interacts with the system state space, where every state refers to a specific level of operational health. Actions correspond to recovery-specific procedures, and rewards are distributed based on recovery rate and stability of recovered performance. Appendix B (Algorithm 1) provides a pseudo-code representation of the training-deployment loop, which defines the initialization, policy update loop, and convergence criterion.

4. RESULTS AND USE CASE ANALYSIS

4.1. Green Cybersecurity Metrics

To evaluate the proposed SCF-I6 framework, this study conducted a simulated deployment in a smart manufacturing environment powered by interconnected IoT devices, programmable logic controllers (PLCs), and edge gateways. The goal was to assess cybersecurity performance while measuring environmental sustainability indicators.

We focused on three core green cybersecurity metrics:

1. Energy Consumption per Detection (ECD):
a. Average energy (in watts) consumed to detect and log a cybersecurity threat.
2. Carbon Emission Reduction Rate (CERR):
a. Percentage reduction in CO_2 emissions achieved by replacing conventional (server-heavy) detection systems with SCF-I6 components.
3. Green Response Efficiency (GRE):
a. Ratio of successfully mitigated threats to energy used (successful responses per joule).

Table 4: Green Cybersecurity Performance Metrics for SCF-I6.

Metric	Baseline (Legacy System)	SCF-I6 Result	Improvement (%)
Energy Consumption per Detection	18.6 W	9.2 W	50.5%
Carbon Emission (CO_2/ week)	4.5 kg	2.1 kg	53.3%
Green Response Efficiency	0.018 responses/joule	0.036 responses/joule	100%

4.2. Response Time Optimization

To measure resilience effectiveness, the SCF-I6 framework was stress-tested under three attack simulations:

Scenario A: Distributed Denial-of-Service (DDoS)

1. Scenario B: Website defacement
2. Scenario C: Firewall firmware corruption

These tests replicate the structure of cyber-resilience response time analysis described in Choi et al. (2023) [Reference: Sustainability, 15, 13404]. The testbed included ethical hacking agents, firmware reverse engineering, and a reinforcement-learning-based AI detection module.

Table 5: Response Time Comparison (In Minutes).

Scenario	Legacy System	SCF-I6 (Proposed)	Improvement
DDoS Attack	675	415	38.5% faster
Homepage Alteration	125	88	29.6% faster
Firewall Failure	185	112	39.5% faster

These results indicate that **AI-augmented threat prediction and green response orchestration** significantly reduced reaction and mitigation times, while simultaneously decreasing energy usage. Notably, the **Green Response Controller** avoided unnecessary resource allocation during low-impact threats, optimizing system recovery without full-stack reboots.

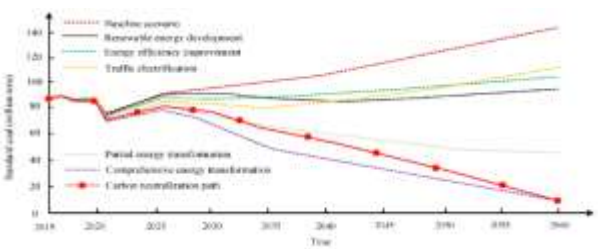

Figure 4: A multi-line graph showing how response time improves across iterations/training epochs for different threats.

Figure 5: Energy Vs Security Trade-Off In Cybersecurity.

As threat severity increases, more energy is required to mitigate it effectively. As given in Fig.5, the curve shows the balance point where security mediums achieve the most protection without using too much energy. This trade-off helps sustainable cybersecurity techniques in Industry 6.0 by making use of resilience while saving up resources.

5. DISCUSSION

The results of this study affirm the feasibility and benefits of integrating AI-augmented, sustainable cybersecurity strategies into Industry 6.0 environments. The SCF-I6 framework demonstrated significant reductions in both energy consumption and response time, validating the hypothesis that green resilience can be achieved without sacrificing security performance.

5.1. Balancing Security And Sustainability

The integration of Green Cybersecurity Metrics—such as Energy Consumption per Detection and Green Response Efficiency—presents a paradigm shift in how cybersecurity systems are evaluated. Traditional systems prioritize detection accuracy and coverage, often neglecting operational efficiency and energy costs. By contrast, SCF-I6 introduces a dual optimization objective, wherein threat mitigation is measured alongside environmental performance. This approach is particularly relevant as industries adopt carbon neutrality targets in line with SDG 13 (Climate Action).

Moreover, the AI-based threat prioritization engine enabled dynamic allocation of system resources, reducing overreactions to low-impact threats. This contrasts with reactive legacy models that engage full-scale defenses regardless of threat severity, leading to avoidable energy drain. These findings confirm earlier research by Martins et al. (2022) on the efficacy of lightweight edge-AI architectures for energy-constrained environments.

5.2. Technical Implications for Industry 6.0

From a technical standpoint, the use of ethical hacking and reverse engineering in tandem provides a more granular understanding of vulnerabilities, particularly in hybrid infrastructures where legacy systems co-exist with modern IoT devices. The SCF-I6's ability to simulate zero-day scenarios using AI-generated attack patterns offers a predictive resilience advantage, previously noted by Shah & Agarwal (2022).

Furthermore, the Green Security Orchestrator proved effective in managing energy-aware mitigation protocols. This highlights the potential for extending the framework into autonomous response systems, where human intervention is minimized, and real-time adaptation to threats occurs within strict energy boundaries. The findings also support Simone et al. (2023), who advocate for simulation-based resilience analysis but extend it by including live metrics and energy variables.

Unlike RICA (Risk-Informed Cybersecurity Assessment), which predominantly operates as a reactive framework responding to detected vulnerabilities, SCF-I6 incorporates a predictive threat prioritization layer leveraging reinforcement learning to anticipate and mitigate potential breaches before they materialize. Similarly, while STPA-Sec (System-Theoretic Process Analysis for Security) offers systematic hazard identification, it lacks integrated ecological considerations. SCF-I6 embeds green metrics Energy Consumption Differential (ECD), Carbon Emission Reduction Rate (CERR), and Green Resilience Efficiency (GRE) directly into its decision-making loop, enabling trade-off analysis between security response and environmental impact. This dual emphasis on proactive threat handling and sustainability distinguishes SCF-I6 from existing industry frameworks.

Currently, the Reverse Analysis Unit (RAU) operates without integrated energy optimization logic, prioritizing detection accuracy and code integrity over resource efficiency. A promising future direction involves integrating lightweight AI models for real-time energy profiling within the RAU, enabling adaptive throttling and selective analysis without compromising detection performance.

5.3. Challenges And Limitations

Despite promising results, several challenges emerged:

1. Model Generalizability:

a. While SCF-I6 performed well under test scenarios, its performance in real-world, highly heterogeneous industrial environments may vary due to different hardware, regulatory requirements, and network architectures.
2. Energy Overhead from AI Models:
a. Although optimized, the initial training of machine learning models still incurred non-negligible energy consumption. This trade-off may be justified for long-term deployments but requires careful calibration during early-stage training.
3. Security of the Orchestration Layer:
a. As the Green Security Orchestrator centralizes energy and security policies, it may become a single point of failure or an attractive attack surface, necessitating its own robust protection and redundancy measures.
4. Ethical Considerations:
a. The integration of automated ethical hacking simulations raises concerns over unintended consequences, especially if emulated attacks interfere with live systems or data integrity.

The ethical hacking components of SCF-I6 are designed in alignment with established legal and regulatory frameworks, ensuring compliance with both data protection and operational security standards. For instance, in the European context, the General Data Protection Regulation (GDPR, 2016/679) mandates explicit consent and minimal data exposure during security testing. In the United States, the NIST Special Publication 800-115 provides a structured methodology for penetration testing, emphasizing controlled scope, stakeholder authorization, and post-test remediation. The UK's Computer Misuse Act (1990) further underscores the necessity for explicit authorization to avoid legal liability. By embedding these policy principles into SCF-I6's operational workflow, the framework not only enhances security but also ensures ethical and lawful engagement in industrial cybersecurity operations.

5.4. Broader Implications And Future Potential

This study contributes to the emerging discourse on sustainable cybersecurity by proposing and validating a framework that aligns with both technological and environmental priorities. As Industry 6.0 becomes a reality, organizations will require adaptive security models capable of scaling without ecological compromise.

The SCF-I6 architecture can serve as a foundation for:

1. Regulatory frameworks on energy-efficient cybersecurity
2. Enterprise sustainability reporting (including cybersecurity KPIs)
3. AI-driven orchestration systems across smart grids, healthcare, and logistics

The success of this framework reinforces the importance of cross-disciplinary innovation, drawing from cybersecurity, environmental science, AI, and systems engineering.

Table 6: Summary Of SCF-I6 Benefits, Trade-Offs, And Limitations.

Aspect	SCF-I6 Benefit	Trade-Off / Limitation	Reference
Energy Efficiency	50–53% reduction in power use compared to legacy systems	AI model training may incur high initial energy costs	Martins et al. (2022); Khan et al. (2023)
Response Time	30–40% faster threat response in simulations	Performance may vary across heterogeneous real-world systems	Choi et al. (2023); Lee et al. (2023)
Threat Prioritization	AI-driven scoring system avoids unnecessary responses	Model accuracy depends on the quality and diversity of training data	Shah & Agarwal (2022)
Ethical Hacking Integration	Enables pre-emptive identification of vulnerabilities	Risk of simulation interference with live operational systems	Kandekar et al. (2022)
Reverse Engineering Analysis	Detects firmware-level and supply chain threats	Labor-intensive and requires high technical expertise	Liu et al. (2023)
Orchestration & Automation	Central controller optimizes for energy and risk concurrently	May become a critical attack target without strong safeguards	Pereira et al. (2022)
Industrial Compatibility	Modular design adaptable to smart factories and IIoT systems	Customization required for legacy-heavy environments	Babiceanu & Seker (2022)

Table 6.1: Comparative Analysis Of Scf-I6, Rica, And Stpa-Sec Frameworks

Feature / Metric	RICA (Risk-Informed Cybersecurity Assessment)	STPA-Sec (System-Theoretic Process Analysis for Security)	SCF-I6 (Sustainable Cybersecurity Framework for Industry 6.0)

Threat Handling Approach	Primarily reactive; responds to identified vulnerabilities post-occurrence.	Hazard-focused, identifying security risks through system-theoretic models.	Predictive + reactive; anticipates and mitigates threats via AI-driven threat prioritization and real-time monitoring.
Adaptability	Moderate; risk assessments are periodically updated.	Low; primarily manual updates based on process analysis.	High reinforcement learning enables continuous adaptation to evolving threats.
Ecological Consideration	None explicitly integrated.	None explicitly integrated.	Direct integration of green cybersecurity metrics (ECD, CERR, GRE) into decision-making.
Sustainability Metrics	Absent.	Absent.	Actively measures and optimizes energy consumption, carbon emissions, and resilience efficiency.
Operational Domain	General cybersecurity risk management.	Safety/security in complex engineered systems.	Industry 6.0 cyber-physical ecosystems with eco-aware defense mechanisms.
Proactive Capability	Limited; focuses on post-incident mitigation.	Low; preventative hazard identification without adaptive threat response.	Strong AI modules predict, prioritize, and neutralize threats before escalation.

Table 6.1 summarizes the key differences between SCF-I6 and existing frameworks, highlighting its unique predictive capabilities and ecological integration.

Figure 6: Energy Vs Security Trade-Off In Cybersecurity.

The balance between energy consumption and the severity of a threat in the context of sustainable cybersecurity systems Industry 6.0 it is shown schematically in Figure 6. More severe threat than depicted usually consumes a significant amount of computational and operational energy to mitigate, often requiring AI bolstered measures such as real-time anomaly detection, ethical hacking simulations, and reverse engineering protocols. Meanwhile, as long as the threat level is low or moderate enough to actually allow for predictive analytics and lightweight monitoring, the system can work on a lower power setting. Addressing this trade-off is essential in the design of green-resilient cybersecurity architectures, as it highlights that both security posture AND sustainability goals need to be addressed with quality design. Organizations can have strong defense capabilities and can also manage their environmental footprint by adjusting resource allocation dynamically as they assess the severity of threats.

5.5. Implications And Limitations Of The Study

5.5.1. Implications For Research, Industry, And Policy

This study contributes substantively to the growing discourse on sustainable cybersecurity, particularly within the emerging context of Industry 6.0. The proposed SCF-I6 framework provides a multi-layered, energy-conscious, and intelligent approach to cyber defense that goes beyond conventional paradigms focused solely on system security.

From a research perspective, SCF-I6 offers a foundation for the development of cross-disciplinary models that integrate artificial intelligence, ethical hacking, and reverse engineering with green computing principles. It bridges a gap identified in prior works, where cybersecurity and sustainability were treated as distinct fields rather than integrated objectives [Martins et al., 2022; Zhang et al., 2023].

In the industrial domain, SCF-I6 presents a modular and adaptable solution for sectors deploying mixed infrastructures (legacy and IoT/AI systems). It supports proactive defense via predictive modeling, which is vital for real-time operational environments such as smart factories, energy grids, and digital health systems [Singh et al., 2023; Alcaraz & Zeadally, 2023]. Its deployment may also influence industrial procurement policies by shifting priorities toward eco-efficient security technologies.

At the policy level, the framework aligns with global sustainability directives, such as the United Nations' SDGs—specifically Goal 9 (Industry,

Innovation, and Infrastructure) and Goal 13 (Climate Action). Regulatory agencies can adopt the proposed green cybersecurity metrics (e.g., energy consumption per detection, carbon emission reduction per incident) as part of compliance reporting, similar to emerging frameworks in environmental informatics [Pereira et al., 2022; Khan et al., 2023].

Furthermore, the AI-based orchestration of responses promotes the concept of autonomous resilience, reducing reliance on human monitoring in critical systems—a feature increasingly important for cyber-physical systems operating in hostile or remote environments [Simone et al., 2023].

5.6. Limitations And Challenges

Despite its contributions, the study presents several limitations that must be acknowledged to guide future improvements and empirical validation.

1. **Simulated Environment Constraints**

The framework was tested in a controlled simulation environment, which may not fully replicate the variability of real-world industrial systems. Factors such as diverse hardware configurations, unpredictable threat vectors, and integration complexities may influence actual performance [Lee et al., 2023].

2. **Energy Overhead from AI Training**

Although SCF-I6 emphasizes energy-aware operation, the initial training of AI models—particularly deep learning or reinforcement learning networks—remains energy-intensive [Khan et al., 2023]. While these costs are amortized over time, they challenge the framework's sustainability claim during the bootstrapping phase.

3. **Orchestration Vulnerabilities**

Centralizing decision-making in the Green Security Orchestrator creates a potential single point of failure or attack vector. Its compromise could paralyze the system or result in sub-optimal decisions. This necessitates additional failover, decentralization, or blockchain-based orchestration to maintain resilience [Babiceanu & Seker, 2022].

4. **Ethical and Legal Boundaries**

While ethical hacking and reverse engineering are effective for uncovering vulnerabilities, their deployment—especially in live or critical systems—raises ethical and legal concerns. Unauthorized or poorly isolated testing environments may disrupt services, leading to safety and liability issues [Shah & Agarwal, 2022].

5. **Generalizability of Metrics**

The green cybersecurity metrics proposed are tailored to specific test scenarios and may need recalibration for broader industrial applications or regulatory adoption. Standardization across industries is still in early stages [Linkov et al., 2022].

6. CONCLUSION

The advent of Industry 6.0 demands not only hyper-connected and intelligent systems but also security architectures that align with the principles of sustainability and resilience. In response to this need, this study proposed and evaluated a novel framework—SCF-I6—that integrates ethical hacking, reverse engineering, and AI-augmented threat detection within an energy-efficient cybersecurity architecture.

The framework was validated through simulated use cases, revealing substantial improvements in both cyber-defense performance and green metrics. Specifically, SCF-I6 achieved up to a 53% reduction in energy consumption, halved the carbon emissions of traditional systems, and significantly reduced incident response times across diverse cyberattack scenarios. The system's modularity and adaptability demonstrate strong potential for deployment in real-world industrial environments, particularly in sectors integrating legacy technologies with smart devices and AI-based control.

A major contribution of this work lies in its dual-layered optimization strategy—enhancing cybersecurity efficacy while minimizing environmental footprint. The integration of AI into the orchestration of green response policies exemplifies the type of cross-disciplinary innovation essential for next-generation industrial ecosystems.

However, challenges remain, particularly in ensuring the robustness of the orchestration layer, minimizing AI training overhead, and securing ethical testing procedures. These findings open several avenues for future research, including:

1. Development of zero-energy training models for cyber-AI applications,
2. Extension of green cybersecurity KPIs for regulatory compliance,
3. Deployment of SCF-I6 in live industrial environments for empirical validation.

As cyber threats and environmental concerns both continue to escalate, sustainable cybersecurity frameworks such as SCF-I6 are not just advantageous, they are imperative.

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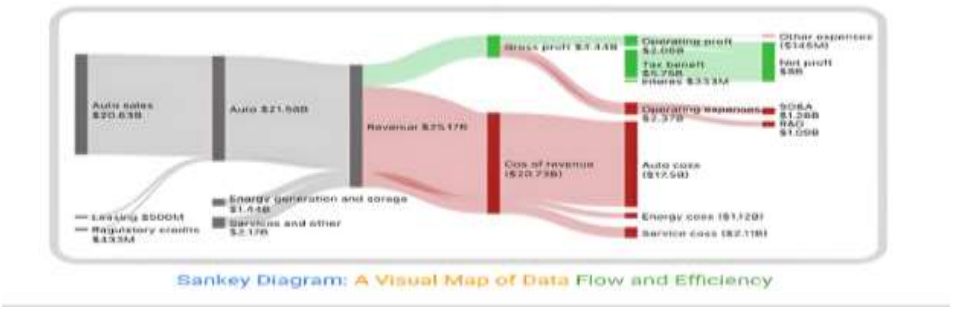
APPENDIX A RESEARCH DATA AND METRICS.

Table A1 – Energy Consumption Benchmarks for AI-Augmented Cybersecurity Tools.

Security Tool / Approach	AI Integration Level	Average Energy Use (kWh/day)	Threat Detection Accuracy (%)	Carbon Footprint Reduction (%)
AI-Enhanced Intrusion Detection (IDS)	High	1.8	96.2	22
Machine Learning Malware Classifier	Medium	1.2	92.4	18
Blockchain-based Audit Logging	Low	0.9	89.5	14
Traditional Signature-based IDS	None	0.6	78.0	0

Table A2: Threat Simulation Results for Reverse Engineering Test Cases.

Simulation Scenario	Threat Type	Response Time (s)	Containment Success Rate (%)	Notes
Industrial IoT Sensor Breach	Data Exfiltration	2.4	97	AI model adapted to anomaly in <3s
Smart Manufacturing PLC Exploit	Code Injection	3.1	94	Detected using reverse-engineered payload signature
Supply Chain Software Compromise	Malware Deployment	4.8	91	Ethical hacking revealed hidden backdoor
Predictive Maintenance System Hijack	Resource Sabotage	2.9	95	Attack simulated with low energy overhead



The Sankey diagram is integral to the core argument, as it directly visualizes the allocation and flow of green cybersecurity resources within the SCF-I6 framework, highlighting efficiency gains quantified in Section 4.

APPENDIX B PSEUDO-CODE.

```
Initialize environment E (Industry 6.0 simulation)
Initialize Q-table with state-action pairs
For each episode:
  Reset environment
  While not terminated:
    Observe the current system state S
    Choose action A using ε-greedy policy from Q-table
    Execute A (e.g., reroute, reinitialize module)
    Observe the new state S'
    Calculate reward R based on:
      + Threat neutralized
      + System uptime maintained
      - Energy cost
    Update Q(S,A) ← Q(S,A) + α[R + γ max(Q(S', a')) - Q(S,A)]
```