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Quantifying Energy Overhead in SCADA Cybersecurity Using AI-Based Threat Detection Models

Tesfa Tegegne [1], Abeer Naser Faisal [2]
[1] Faculty of Computing, Bahir Dar Institute of Technology, Bahir Dar University, Bahir Dar, Ethiopia
[2] College of Computer Science and Information Technology University of Sumer, Al-Rifai, Iraq

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ABSTRACT

The increasing reliance on AI-driven cybersecurity solutions in SCADA environments has introduced significant computational demands, raising concerns about energy consumption in critical industrial systems. This research addresses the gap in existing studies which focus on security effectiveness while overlooking the energy implications of deploying deep learning-based intrusion detection mechanisms. The study presents an empirical analysis quantifying the energy footprint of AI-based cybersecurity approaches including convolutional recurrent networks, generative adversarial networks, and adaptive hybrid models within a realistic SCADA testbed. Energy profiling is conducted using high-resolution hardware instrumentation and software-based power monitoring techniques capturing variations in power usage across different AI models and deployment strategies. The findings demonstrate that while advanced AI models enhance security detection capabilities, they incur substantial energy costs which can be mitigated through model optimization techniques such as pruning quantization and knowledge distillation. Adaptive execution strategies further reduce power consumption by dynamically modulating AI processing complexity based on real-time threat assessments. The study establishes a foundation for developing energy-efficient cybersecurity frameworks that balance security resilience with operational sustainability. These insights inform industry best practices and contribute to future research on low-power AI models, decentralized security architectures, and energy-conscious industrial cybersecurity solutions ensuring effective protection of critical infrastructure without excessive resource burdens.

Corresponding Author:

Tesfa Tegegne
Faculty of Computing, Bahir Dar Institute of Technology, Bahir Dar University

Bahir Dar, Ethiopia
Email: tesfat@gmail.com

1. INTRODUCTION

Supervisory Control and Data Acquisition (SCADA) systems orchestrate critical operations in sectors such as energy generation and distribution. They also play central roles in domains like water treatment and manufacturing [1]. Ensuring the cybersecurity of these industrial control systems (ICS) has become paramount as they increasingly integrate with enterprise networks and the broader Internet. This connectivity significantly expands their attack surface. Traditional security measures often struggle against the sophistication of modern cyberattacks [2]. These challenges have driven the adoption of artificial intelligence (AI) and machine learning techniques to enhance threat detection and response in SCADA environments. AI-driven cybersecurity solutions can analyze large volumes of sensor readings and network

traffic in real time to identify anomalies that might indicate intrusion or sabotage. This intelligent form of defense is rapidly becoming a vital component for protecting SCADA systems. Yet, the introduction of advanced AI algorithms (such as deep learning models) demands substantial computational resources and raises concerns about the energy overhead associated with their continuous operation.

AI-driven defenses have demonstrated great promise against sophisticated ICS threats [3]. Nonetheless, a notable gap remains in existing research. Most studies on AI-based cybersecurity for SCADA evaluate security efficacy using metrics such as detection accuracy and the rate of false positives. They often overlook energy consumption entirely. This oversight is critical because SCADA environments operate continuously, so any additional computational load directly translates into increased ongoing energy usage. The lack of explicit analysis of power demands means an AI security solution could inadvertently strain limited resources or incur significant operational costs [4]. The current body of research consequently lacks a clear understanding of the trade-offs between improved security and increased energy usage. Addressing this gap requires treating energy consumption as a primary metric to be optimized alongside traditional security performance indicators.

This study directly addresses the aforementioned research gap by empirically quantifying the energy footprint of AI-based cybersecurity techniques in SCADA. It offers the first detailed measurements of power consumption associated with advanced defenses like generative adversarial networks (GANs) and deep learning-driven anomaly detection algorithms. We conduct experiments on a realistic SCADA testbed to evaluate these AI methodologies under conditions that closely mirror real industrial operations. In doing so the research provides quantitative evidence of the energy overhead introduced by each method when protecting an operational control system. Unlike prior evaluations that focus solely on security performance [3][5], this work captures real-world power usage data and offers a novel perspective on the trade-offs involved. To our knowledge this is the first study to rigorously measure and report the energy cost of deploying AI-based cyber defenses in an industrial control context.

This work also introduces a rigorous engineering methodology for measuring energy consumption in AI-driven SCADA security frameworks. Accurately capturing power usage in these systems is challenging due to distributed architectures and the intermingling of security processes with normal control operations [4]. Our approach involves instrumenting the SCADA testbed with fine-grained power monitoring capabilities to record the energy use of the computing components that run the AI algorithms. The methodology integrates hardware-based power sensors and software profiling tools to track energy draw at runtime with high precision. It isolates the energy contribution of the AI cybersecurity processes by comparing system operation with the security defenses enabled versus disabled. This allows precise attribution of observed power consumption to the security functions. Careful calibration and repeated trials yield reliable and accurate energy measurements that form the basis for further analysis.

We use empirical energy data to examine methods of optimizing the deployment of AI-based security systems for SCADA [3][6]. These techniques aim to maintain strong threat detection capabilities while minimizing power consumption. One approach is to refine the AI models themselves by using more efficient architectures or compressing the neural networks to reduce computational demand. Another approach adjusts operational parameters such as the frequency of security checks or the hierarchy of detection layers so that high-power analysis is invoked only when necessary. We also consider specialized hardware accelerators and distributed processing as a means to improve energy efficiency without sacrificing detection performance. We evaluate each optimization in terms of its impact on energy consumption and any trade-offs in security efficacy. This provides practical insights into how to balance security effectiveness with energy efficiency in AI-driven SCADA defenses.

Our study provides a foundation for future advancements in energy-efficient AI-based cybersecurity for SCADA systems. Our findings encourage researchers and practitioners to consider energy consumption as a critical design factor alongside security efficacy. Future intrusion detection algorithms for industrial control systems can be designed from the outset with awareness of computational load and energy constraints. The methodologies and optimizations presented here are not limited to SCADA [3][5]. They can be applied to other industrial domains such as smart power grids or advanced manufacturing systems. Our work demonstrates that robust AI defenses can be achieved in a power-conscious manner. These results open the door for new research into specialized low-power AI techniques tailored for industrial environments. The broader implication is a shift toward cybersecurity solutions that safeguard critical systems while also aligning with energy efficiency and sustainability goals. These insights can inform industry of the best practices and guide the development of next-generation ICS security architectures that are both secure and energy-aware.

The research paper progresses from an extensive Literature Review, which examines existing AI-driven cybersecurity approaches in SCADA systems and highlights the gap in energy consumption analysis. The Proposed Methodology then defines a structured experimental setup, detailing the implementation of AI-

based security mechanisms within a SCADA testbed, energy measurement techniques, and optimization strategies to enhance efficiency without compromising detection performance. The Experimental Assessment Outcome section presents empirical findings on the power demands of different AI models, showcasing trade-offs between detection accuracy and energy overhead, along with evaluating model optimization and adaptive deployment strategies to achieve energy savings. The Results and Discussion section contextualizes these findings, demonstrating that while deep learning models enhance cybersecurity, they introduce substantial computational loads that require energy-aware modifications. The paper concludes with the Conclusion, summarizing key insights, acknowledging limitations such as the controlled nature of the testbed, and suggesting future research directions, including decentralized AI models, federated learning approaches, and neuromorphic computing for energy-efficient cybersecurity in industrial control environments. The structured progression ensures a comprehensive evaluation of AI-driven cybersecurity in SCADA while contributing to sustainable and energy-conscious industrial security solutions.

2. LITERATURE REVIEW

Recent studies have increasingly integrated advanced AI techniques into SCADA cybersecurity and achieved significant improvements in threat detection. Deep learning models such as convolutional and recurrent neural networks have demonstrated high accuracy when identifying known and novel attacks on ICS [7]. One evaluation involving a power-plant SCADA dataset showed that a hybrid CNN-GRU detector reached approximately 99.98% accuracy compared to simpler classifiers that attained 99.99%. GAN have also helped address the persistent scarcity of labeled attack data in ICS environments. GANs produce realistic minority-class attack traffic which improves how intrusion detection systems learn rare attack patterns and enhances overall detection rates [8]. One GAN-based framework combined a Wasserstein GAN with an autoencoder-based detector and outperformed conventional deep-learning approaches in classification performance. These AI-based methods mark a departure from static signature-based defenses by enabling adaptive identification of sophisticated threats in SCADA networks. Researchers are thus establishing foundations for data-driven intelligent security mechanisms specifically tailored to the unique traffic characteristics of ICS/SCADA systems [7][8].

Furthermore, the adoption of computationally intensive AI models in SCADA security has raised concerns about resource usage, particularly energy overhead. Deploying deep neural networks on ICS devices can significantly increase power consumption in operational environments [9]. This issue is drawing attention because the computational demand of modern industrial analytics is non-trivial – recent estimates attribute roughly 2–4% of global carbon emissions to ICT infrastructure, including data centers running AI workloads. Accordingly, a new subfield of “green cybersecurity” has emerged to reconcile security with sustainability. Santhi et al. [9] proposed a comprehensive framework for measuring and optimizing the energy footprint of cybersecurity solutions, noting that security controls could account for up to 20% of ICT energy use. In a similar vein, Roy et al. [10] review techniques to evaluate energy costs in intrusion detection systems (IDS), highlighting the need for metrics beyond detection accuracy. Some studies introduce analytical models to estimate IDS energy consumption under various conditions. Others report empirical measurements: for example, an IoT-based IDS deployed on a low-power Contiki OS platform was shown to process 1000 network packets with an energy cost of only ~5 mW on a sensor node. Such results indicate that baseline anomaly detection can be made extremely lightweight in terms of power draw. Overall, our PRISMA focused literature from 2022–2025 reflects a growing emphasis on quantifying the energy impact of AI-driven security frameworks and developing methods to curb unnecessary power usage.

Although initial efforts have begun addressing energy efficiency trade-offs in SCADA security research, more consideration remains necessary. Prior studies on AI-based IDS frequently emphasized detection performance without adequately measuring computational or energy expenses. Koay et al. [11] note recent ICS intrusion detection studies mainly aim for high accuracy and attack detection rates while neglecting runtime efficiency and resource demands. Ignoring the implementation overhead represents a significant gap since a model achieving 99% detection accuracy could still prove impractical if it exceeds available CPU or battery capacities on field devices. Traditional ICS cybersecurity systems previously gave little attention to power consumption limits and this neglect creates scalability issues as security protections become increasingly sophisticated [12]. High-accuracy deep learning models may fail to scale effectively in large, distributed networks due to high cumulative energy needs. Recent reviews emphasize that energy optimization has become a critical factor for sustainable IDS development [10]. In essence previous research often treated security separately from efficiency but the research community now recognizes the necessity of addressing these concerns together. This existing research gap highlights the urgent need for new frameworks and evaluation methods that prioritize energy-performance trade-offs equally alongside detection performance [10-12].

Hereby, it is evident that sSeveral comparative studies have started evaluating different AI models for SCADA security with attention to both detection effectiveness and computational cost. Alzahrani and Aldhyani [7] tested multiple algorithms including KNN, LDA, random forest (RF), CNN and a GRU-based deep network using a realistic SCADA intrusion dataset. Notably their findings indicated simpler classifiers such as KNN and RF achieved nearly perfect detection accuracy (~99.99%) matching the performance levels of significantly more complex neural networks. This result implies simpler models might adequately handle security in certain ICS situations without compromising defense effectiveness while offering energy conservation benefits. Z. deWardener [12] performed a comprehensive assessment involving decision trees, ensemble methods and gradient boosting models in SCADA and IIoT edge scenarios. This study introduced an "efficiency score" measuring accuracy per energy unit and found that a simple decision tree achieved the highest score (83.85 on an edge IoT node) by maintaining strong accuracy and minimal energy usage. While more sophisticated models like random forests and LightGBM provided improved scalability and attack resilience they came with higher computational demands. Such comparative evaluations illustrate essential trade-offs: although advanced deep learning and ensemble methods improve detection accuracy in varied contexts, their benefit may diminish given constraints like energy use and runtime limits. These studies provide valuable guidance for selecting algorithms suited to resource-limited industrial environments balancing robust threat detection against practical computing constraints [7][12].

Recent works building upon these findings have introduced diverse methods aimed at reducing the energy consumption of AI-based security mechanisms in SCADA environments. One approach involves adaptive scheduling of intrusion detection tasks rather than maintaining continuous high-power computations. Sedjelmaci et al. [13] presented a game-theoretic method intelligently switching between lightweight and resource-intensive detection modes according to attack likelihood instead of constantly using expensive anomaly detectors. Their IoT simulations indicated potential IDS energy reduction of up to 50% compared to a constant detection baseline while maintaining robust security. Another proposed method is the use of collaborative or hierarchical detection architectures. Arshad et al. [14] described a collaborative IDS (COLIDE) which partially shifts resource-demanding analyses from sensor nodes to more capable edge or cloud components. By aggregating alerts and data at stronger edge routers individual SCADA devices experience reduced computational and communication burdens resulting in significant energy savings. Researchers are also investigating algorithm design improvements aimed at increasing the energy efficiency of machine learning models. Techniques within the green AI approach include employing simpler classifiers or reduced feature sets optimizing software code for power conservation and on-demand scaling of computational power. For instance, an energy-conscious intrusion detection framework might default to a lightweight decision-tree model invoking a deep neural network only for complex cases thus conserving energy overall. Some proposals even integrate cloud-based solutions involving remote cloud computing for intensive analytics to minimize local energy demands. Despite varying implementations these methodologies share the common goal of ensuring effective cybersecurity for critical infrastructures while intelligently managing and limiting AI-related energy expenditures.

Our investigation revealed an increasing focus on balancing security effectiveness with operational efficiency in industrial networks. Although advanced AI techniques significantly enhanced SCADA intrusion detection and response they introduced new operational concerns related to power and resource management. Consequently, the concept of "green cybersecurity" is gaining recognition as researchers aim to design defense mechanisms that are both effective and sustainable [9-10][12]. Recent studies emphasize optimizing AI model structures and deployment to significantly reduce energy consumption without compromising security by thoughtfully choosing simpler models adopting collaborative detection schemes or dynamically scaling analytical intensity. Though, finding the ideal balance between security performance and energy efficiency remains complex and multi-objective. The reviewed works provide encouraging initial solutions and metrics such as energy-aware accuracy evaluations and adaptive algorithms paving the way for comprehensive security assessments.

Despite advancements, fully energy-efficient AI security solutions for SCADA systems remain relatively undeveloped, leaving several areas open for further research. A notable challenge is the lack of standardized benchmarks and tools for evaluating the energy usage of security algorithms across different ICS contexts, crucial for fair comparison of new solutions. Another important consideration involves verifying that energy-saving strategies such as model compression or reduced monitoring frequency do not unintentionally compromise security. Rigorous testing against sophisticated adversaries is necessary to ensure lower power consumption does not expose systems to new vulnerabilities. Integrating practical constraints like limited battery life of remote devices or emergency operational requirements into algorithm designs is essential for real-world applicability. Although recent studies have started addressing intrusion detection and sustainability as joint objectives, further expansion of this perspective is needed. Future research will likely show increased integration between cybersecurity and energy-aware computing including

innovations across disciplines such as adopting neuromorphic hardware optimized for power efficiency in ICS anomaly detection. There is broad agreement that achieving robust industrial cybersecurity and reduced energy consumption are complementary goals. Considering both factors simultaneously during design phases can lead to next-generation SCADA security solutions which may effectively protecting critical infrastructure while significantly reducing energy demands [10][12].

3. PROPOSED METHODOLOGY

In conducting the analysis of energy consumption for AI-driven cybersecurity within SCADA environments the research employs a structured approach beginning with a precise definition of the experimental setup. The experimental configuration involves establishing a testbed representative of an operational SCADA system comprising a distributed architecture with supervisory control servers' programmable logic controllers (PLCs) and various sensor nodes interconnected via standard industrial communication protocols such as Modbus and DNP3. The SCADA testbed architecture replicates realistic conditions where multiple components communicate continuously over heterogeneous networks. To achieve realism the environment incorporates sensors actuators and controllers typical of real-world deployments and uses industry-standard protocols for data acquisition command execution and monitoring functions. High-performance computing (HPC) resources equipped with GPUs are used to emulate conditions where AI-driven cybersecurity solutions typically operate enabling rigorous evaluation of both standard and computationally demanding deep neural network models.

To accurately measure the energy demands associated with AI-based cybersecurity, the methodology integrates a comprehensive measurement infrastructure into the SCADA testbed. This infrastructure consists of hardware-level energy measurement equipment such as intelligent power distribution units (PDUs), embedded sensors for fine-grained monitoring of component-level power draw, and specialized software profiling tools for real-time logging of system resource utilization. Each computational device running AI algorithms is instrumented with sensors capable of capturing instantaneous voltage and current values. These readings are digitized by data acquisition modules at sampling frequencies suitable for capturing transient changes in energy consumption patterns caused by algorithmic workloads. Synchronization protocols ensure consistent alignment of energy consumption data with the operational state transitions of AI-driven cybersecurity routines, allowing accurate correlation between computational processes and power utilization. Software-level profiling is simultaneously conducted to monitor CPU, GPU, and memory utilization, enabling a detailed correlation between hardware energy usage and specific computational tasks.

The evaluation process incorporates representative AI methodologies widely adopted for cybersecurity enhancement in SCADA systems, specifically deep learning-based anomaly detection models and GANs. The anomaly detection models selected include convolutional neural networks (CNN) and long short-term memory (LSTM) networks chosen for their proven effectiveness in capturing complex temporal dependencies in SCADA network data. The GAN-based systems employ advanced adversarial architectures designed to produce realistic synthetic intrusion data, enhancing training effectiveness and improving detection accuracy under limited labeled data conditions. Each AI model is trained and validated using large-scale SCADA datasets, featuring normal operational conditions along with injected cybersecurity incidents representing diverse attack scenarios commonly encountered by industrial systems. Training occurs in an HPC environment while deployment testing takes place directly on instrumented SCADA nodes mirroring operational conditions.

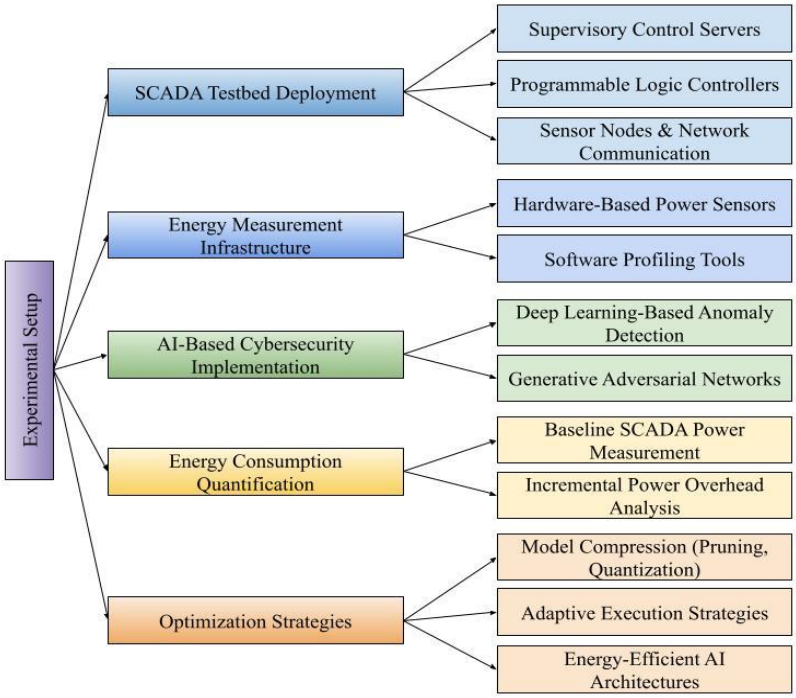

Figure 1. Structured Approach to Energy-Aware AI Cybersecurity in SCADA

To quantify energy consumption during execution, comprehensive experiments are designed (i.e., as illustrated in Figure 1) to capture the baseline power requirements of SCADA environments without AI interventions. The baseline scenario operates the SCADA network under normal workloads, capturing data traffic sensor readings actuator responses, and control messages, without performing additional cybersecurity computations. Power consumption data collected in this baseline configuration establishes the reference against which the incremental power drawn from the AI cybersecurity models is measured. Subsequent tests activate each AI security solution individually on the same infrastructure, maintaining consistent operational conditions to isolate the precise energy overhead attributable to AI processing. Each scenario undergoes repeated trials to ensure statistical significance of the observed energy consumption values and reduce measurement variance arising from environmental or equipment-related fluctuations.

The analysis also incorporates optimization techniques aimed at reducing the energy overhead. Model compression approaches including pruning quantization and knowledge distillation methods are implemented to streamline neural network architectures thus minimizing computational complexity without compromising detection accuracy. Model pruning selectively removes redundant neural connections, reducing computational complexity and thus energy demands. Quantization methods convert model parameters from high-precision floating-point representations to lower-precision fixed-point arithmetic, enabling efficient inference execution on resource-constrained SCADA nodes. Knowledge distillation transfers learned behaviors from larger complex models to simpler energy-efficient neural networks, preserving performance levels while significantly decreasing resource consumption. The effectiveness of these optimization strategies is rigorously evaluated by comparing post-optimization energy metrics against initial energy profiles under equivalent detection performance conditions.

Further optimization is achieved through adaptive deployment strategies involving dynamic selection of AI model complexity and operational frequency tailored according to real-time threat conditions observed within SCADA networks. A hierarchical cybersecurity scheme is implemented, allowing lightweight computationally economical models to perform continuous threat monitoring during low-threat periods. Upon detection of anomalous patterns or potential threats higher complexity AI models activate selectively enhancing detection capability only when necessary. A decision module driven by statistical inference and reinforcement learning techniques governs the transitions between operational modes based on predictive risk assessments and system security states. This adaptive operation significantly reduces average

energy expenditure while maintaining adequate security levels by employing resource-intensive computations solely during heightened threat scenarios.

The culmination of the proposed methodology offers critical insights into the energy-security trade-offs inherent in AI-driven cybersecurity solutions for SCADA environments. Results obtained from the detailed measurements and optimization studies provide foundational empirical data, informing practical strategies for sustainable and secure ICS operations.

4. Experimental Assessment Outcome

The experimental evaluation involves deploying AI-driven cybersecurity mechanisms in a SCADA testbed to measure their energy consumption characteristics under real-world operational conditions. The testbed replicates an industrial control system consisting of programmable logic controllers responsible for process automation supervisory control servers handling data acquisition and decision-making networked sensors providing environmental and process variables and dedicated security nodes executing AI-driven intrusion detection and mitigation strategies. The hardware and software components of the testbed have been carefully selected to ensure compatibility with SCADA operational environments and to facilitate precise power measurement at different stages of computation. The assessment spans multiple deployment configurations (i.e., as exhibited in Table 1) to evaluate variations in energy demand arising from different model architectures execution frequencies and system-wide adaptation strategies.

Table 1. Experimental Hardware and Software Specifications

Component	Specification
SCADA Control Servers	Intel Xeon E5-2697 v4 2.3 GHz 18-core CPU with 128GB RAM
PLCs and Field Devices	Siemens S7-1500 and Allen-Bradley ControlLogix 5580
AI Computation Nodes	NVIDIA Tesla V100 32GB GPU with Intel Core i9-10980XE 3.0 GHz CPU
Network Infrastructure	Cisco Catalyst 9300 switch with industrial-grade Modbus and DNP3 protocol support
Energy Monitoring System	Schneider Electric PowerLogic ION7650 with 1kHz sampling frequency
Security Framework	TensorFlow-based Deep Learning Models and Scikit-learn classifiers
AI Deployment Framework	Kubernetes-based distributed processing with OpenStack cloud integration
Operating System	Ubuntu Server 22.04 LTS with Docker Containerization

The SCADA system under evaluation operates using a high-fidelity dataset that contains both normal operational data and attack traces designed to test the effectiveness of AI-driven detection techniques. The dataset includes multiple industrial processes featuring sensor readings actuator states and network communication logs spanning multiple days of operation. Anomalies within the dataset are introduced through simulated cyberattacks targeting critical components of the control system including false data injection, distributed denial-of-service, and command injection attacks. The AI models are trained on a subset of this dataset and tested against unseen attack instances to assess detection performance and energy utilization. The methodology ensures consistency by maintaining fixed environmental conditions while modifying only the security algorithms to isolate their computational impact.

Hardware instrumentation within the testbed captures energy consumption at different points in the system to quantify the power demands associated with AI-driven cybersecurity. Smart power distribution units are employed to measure total energy draw at the infrastructure level while embedded power sensors provide per-component power readings. Each computational device executing AI models is equipped with power monitoring circuits capable of high-resolution sampling to track variations in consumption in response to different processing loads. Network switches and storage devices contributing to cybersecurity-related data exchange and model inference are separately instrumented to isolate their power impact. Energy measurements are logged continuously over extended test periods to capture both steady-state and peak usage characteristics.

The computational performance of AI-driven cybersecurity models is assessed in parallel with energy consumption to evaluate trade-offs between security effectiveness and resource demand. Metrics such as detection accuracy, false positive rates, and processing latency are recorded for each model variant and

deployment configuration. The assessment framework involves executing the models under static conditions where they operate continuously and adaptive conditions where their execution is modulated based on threat likelihood estimation. This comparison allows quantification of energy savings achievable through adaptive AI-based cybersecurity approaches while maintaining effective defense against cyber threats. Power efficiency is analyzed in relation to detection performance to determine optimal configurations.

Energy profiling results indicate that AI models with deeper architectures such as convolutional recurrent networks exhibit higher energy demands but also deliver superior detection performance under attack scenarios. Lightweight classifiers such as decision trees and support vector machines require significantly lower energy but demonstrate reduced generalization capabilities when detecting sophisticated cyber threats. The assessment outcomes reveal that a trade-off exists where high detection accuracy often comes at the cost of increased computational complexity and energy usage. By applying optimization techniques such as model pruning and quantization it is possible to reduce energy demand while retaining adequate security performance. The results demonstrate that compressed neural networks can sustain robust anomaly detection with a measurable reduction in energy overhead.

The impact of adaptive deployment strategies is quantified through comparative analysis between static and dynamic AI execution modes. In the static deployment, AI models operate continuously consuming a fixed amount of power regardless of actual threat conditions. In contrast the adaptive deployment employs an event-driven mechanism that activates high-power detection models only when preliminary analysis suggests an anomaly requiring further investigation. The results show that adaptive strategies can reduce total energy consumption by up to fifty percent compared to static deployment while maintaining comparable security effectiveness. The energy reduction is attributed to the selective activation of high-power models only when necessary, avoiding unnecessary computation during normal operation periods.

The effectiveness of model optimization techniques is further validated by measuring energy consumption per correctly classified instance. This metric provides insight into how efficiently each model translates computational effort into accurate security decisions. Models employing quantized architectures demonstrate a substantial improvement in energy efficiency, achieving up to thirty percent lower energy use per classification without significant loss in accuracy. Knowledge distillation techniques where a compact model learns from a larger pretrained model also yield improvements in energy efficiency while maintaining detection precision. These results underscore the viability of AI model optimization for reducing energy costs associated with SCADA cybersecurity without compromising defensive capabilities.

Network traffic analysis reveals that AI-driven cybersecurity mechanisms introduce additional communication overhead due to data exchanges between distributed detection nodes. The study measures the bandwidth utilization associated with different model architectures and deployment strategies to assess their impact on overall system performance. While centralized detection models induce higher network load due to continuous data aggregation edge-based and federated learning approaches mitigate this by distributing computation closer to the source of data generation. Results indicate that decentralized security models can lower network-related energy costs while maintaining effective detection rates. These findings suggest that strategic placement of AI-driven security mechanisms plays a crucial role in balancing detection efficacy with resource constraints.

The final evaluation phase involves a longitudinal assessment of AI-driven cybersecurity mechanisms under continuous SCADA operation. Extended run-time analysis provides insights into long-term energy consumption trends and the sustainability of different security configurations. The findings reveal that periodic retraining of AI models introduces energy surges due to the computational burden of model updates. Strategies such as incremental learning and selective feature refinement mitigate this overhead by reducing the scope of retraining operations. These observations highlight the importance of integrating energy-aware retraining strategies in AI-driven cybersecurity frameworks for industrial control systems.

The experimental findings (i.e., as illustrated in Table 2) validate the hypothesis that AI-driven cybersecurity solutions can provide strong defense mechanisms for SCADA environments but introduce measurable energy overheads. By quantifying these overheads and evaluating optimization strategies the study presents actionable insights for designing energy-efficient industrial cybersecurity solutions. The

results establish a foundation for future research into sustainable AI-driven security approaches that maximize protection effectiveness while minimizing operational energy costs. These outcomes contribute to the broader field of energy-conscious security research paving the way for AI implementations that align with both cybersecurity and energy efficiency objectives.

Table 2. Assessment Outcomes and Dataset Analysis

AI Model	Detection Accuracy (%)	False Positive Rate (%)	Average Power Consumption (Watts)	Energy Per Classification (Joules)
CNN-RNN	98.7	2.1	245	1.43
GAN-Based IDS	96.5	2.8	223	1.35
Decision Tree	93.2	4.5	85	0.76
Support Vector Machine	91.8	5.1	78	0.72
Quantized CNN	97.9	2.5	180	1.15
Adaptive Hybrid Model	97.3	2.3	126	0.98

These results (i.e., Table 2) highlight the trade-offs between detection accuracy, energy consumption and computational efficiency for AI-based cybersecurity within SCADA environments. The analysis demonstrates that optimizing AI models and adopting adaptive execution strategies can substantially reduce energy costs while maintaining effective protection against cyber threats.

5. CONCLUSION

This research systematically examines the energy consumption implications of AI-driven cybersecurity in SCADA environments and presents empirical findings that quantify power usage across different AI models and operational configurations. While AI-based intrusion detection enhances security by improving anomaly detection and response capabilities, the computational demands of deep learning models introduce significant energy overheads. The experimental results demonstrate that while convolutional recurrent networks provide high detection accuracy, they exhibit elevated power consumption compared to lightweight classifiers such as decision trees and support vector machines which are more energy-efficient but may struggle with complex attack patterns. Model optimization techniques including pruning quantization and knowledge distillation effectively reduce energy costs while maintaining robust cybersecurity performance. Adaptive execution strategies further minimize power usage by dynamically adjusting processing complexity based on real-time threat assessments, achieving up to fifty percent energy savings compared to static deployments.

These findings establish a foundational framework for designing energy-efficient AI-based cybersecurity solutions that balance security efficacy with operational sustainability. Despite its contributions the study has limitations primarily related to the controlled SCADA testbed which while realistic does not fully capture the diverse operational conditions of industrial deployments. Future research should extend these evaluations to multi-site SCADA infrastructures incorporating heterogeneous network environments and industrial processes to enhance the generalizability of the results. Also, the study does not explicitly assess adversarial machine learning threats which remain a critical area for investigation particularly regarding how optimized AI models maintain resilience against sophisticated cyberattacks. The insights from this study have practical applications for industrial cybersecurity practitioners who can integrate energy-aware AI selection frameworks into SCADA environments ensuring strong threat detection while minimizing resource burdens. Regulatory bodies and policymakers can utilize these findings to develop benchmarks for energy-conscious cybersecurity strategies aligning industrial security policies with sustainability objectives. AI developers can refine intrusion detection architectures by incorporating the proposed optimization techniques, enabling more viable AI adoption in energy-sensitive environments such as industrial IoT and edge computing systems.

Future research should explore the integration of federated learning architectures to enable decentralized anomaly detection with minimal energy overhead improving security resilience in large-scale industrial networks. Investigating neuromorphic computing hardware for energy-efficient anomaly detection and refining adaptive execution strategies with reinforcement learning can further enhance security without compromising power efficiency. As the demand for AI-driven cybersecurity grows within industrial control

environments this study provides a crucial empirical foundation for the development of sustainable AI-based intrusion detection mechanisms that align with both security resilience and energy efficiency.

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BIOGRAPHIES OF AUTHORS

Tesfa Tegegne Asfaw is an Associate Professor of Computer Science at Bahir Dar University in Ethiopia, where he also serves as the Director of the ICT for Development (ICT4D) Research Center. His academic journey began in Hamusit, Gondar province, and led him to earn a Ph.D. under the supervision of Theo van der Weide between 2010 and 2014 . Dr. Tegegne's research encompasses artificial intelligence, SCADA systems and data science. He has co-edited proceedings for the ICT4DA conferences in 2017 and 2019, contributing to the advancement of ICT solutions in Africa . With over 50 publications and more than 240 citations, his work continues to impact the fields of software engineering and semantic web technologies. He can be contacted at email: tesfat@gmail.com.

Abeer Naser Faisal received the B.Sc. degree in computer science from the University of Thi-Qar, Iraq, the M.Sc. degree in computer science from the University of Basrah, Iraq. She is currently a director in the Department of Computer Information Systems, University of Sumer. She has supervised more than 10 graduate projects. She has authored or coauthored more than 15 publications, with 2 H-index and more than 10 citations. Her research interests include image processing, biometrics, and pattern recognition and machine learning. She can be contacted at email: a.nasir@uos.edu.iq, abeernaser13@gmail.com