# Hybrid Deep Learning for Secure IoT-WSN Environments and Renewable Energy Forecasting Using Tunicate and Rooster Optimization

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## Abstract

In the contemporary era of interconnected intelligent systems, the Internet of Things (IoT) and Wireless Sensor Networks (WSNs) form the backbone of real-time data acquisition, automation, and smart energy management. However, the vast interconnectivity among devices exposes these networks to multifaceted cyber threats and energy inefficiencies, demanding robust, intelligent, and adaptive mechanisms for security and forecasting. This paper introduces a hybrid deep learning framework that unifies Tunicate Swarm Optimization (TSO) and Rooster Optimization Algorithm (ROA) to enhance both cybersecurity in IoT-WSN systems and renewable energy forecasting accuracy. The TSO algorithm improves feature selection and dimensionality reduction, while ROA optimizes the deep neural architecture parameters, leading to superior detection accuracy and energy efficiency. The hybrid model integrates Deep Belief Networks (DBN) and Long Short-Term Memory (LSTM) networks to simultaneously handle temporal dependencies and feature complexities in IoT data streams. The experimental analysis demonstrates that the proposed model achieves significant improvements in intrusion detection rates, energy consumption prediction, and overall computational efficiency compared to existing benchmark techniques. This study provides a comprehensive framework for sustainable, secure, and intelligent IoT-WSN environments, bridging the gap between cybersecurity and renewable energy forecasting within a unified optimization paradigm.

**Keywords:** IoT Security, Wireless Sensor Networks, Renewable Energy Forecasting, Hybrid Deep Learning, Tunicate Swarm Optimization, Rooster Optimization Algorithm, Intrusion Detection, Energy Efficiency

# I. Introduction

The rapid proliferation of IoT and WSN technologies has revolutionized how data is collected, transmitted, and utilized in real-time decision-making [1]. From smart cities and industrial automation to precision agriculture and renewable energy systems, billions of interconnected sensors form vast digital ecosystems. Despite their potential, these networks are highly vulnerable to cyber intrusions, data tampering, and energy inefficiencies due to constrained computational resources and open communication protocols. Thus, maintaining security, accuracy, and sustainability simultaneously becomes a significant challenge in modern IoT-WSN environments. Traditional machine learning-based models often fail to cope with large-scale heterogeneous data and dynamic network conditions, necessitating the introduction of hybrid deep learning paradigms integrated with advanced optimization algorithms [2].

In cybersecurity, deep learning models like DBN and LSTM have shown remarkable capabilities in identifying complex attack patterns by learning hierarchical data representations. However, their performance depends heavily on hyperparameter tuning, which is computationally expensive and prone to local minima issues. Similarly, in renewable energy forecasting, where time-series data are volatile and nonlinear, optimization-driven deep learning models offer greater precision in predicting energy outputs. The integration of bio-inspired optimization algorithms such as Tunicate Swarm Optimization (TSO) and Rooster Optimization Algorithm (ROA) presents a promising solution to enhance both learning and adaptability. These algorithms mimic natural behaviors—TSO emulates tunicates' foraging strategies, while ROA models rooster dominance behaviors—to achieve global exploration and fine-tuned convergence. Furthermore, the convergence of cybersecurity and energy forecasting in IoT-WSN environments is a relatively unexplored domain. Modern smart grids and sensor networks require dual functionality: safeguarding data from malicious attacks and ensuring optimal energy utilization [3]. A hybrid framework that simultaneously optimizes these two objectives can dramatically enhance resilience and performance. Therefore, the proposed research focuses on a dual-objective optimization model that integrates TSO for robust feature extraction and ROA for dynamic learning rate and weight tuning within a hybrid DBN-LSTM structure.

The novelty of this study lies in its cross-domain applicability—leveraging deep learning not just for intrusion detection but also for renewable energy forecasting. By coupling two bio-inspired

optimization methods, the proposed model achieves both security robustness and predictive intelligence, marking a substantial contribution to sustainable IoT-WSN research. The experimental framework validates its performance on publicly available datasets, ensuring reproducibility and real-world applicability [4]. The results underscore the hybrid model's capability to outperform state-of-the-art techniques in accuracy, stability, and adaptability.

## II. Related Work

Recent literature reveals significant efforts to improve IoT-WSN security and energy forecasting using artificial intelligence. Conventional machine learning approaches such as Support Vector Machines, Random Forests, and K-Means clustering have demonstrated reasonable success in identifying basic intrusion types [3]. However, these models struggle to generalize across dynamic IoT ecosystems characterized by noisy and non-stationary data. In contrast, deep learning frameworks have shown superior performance by leveraging hierarchical feature learning. Notably, LSTM networks capture sequential dependencies in sensor data, making them ideal for time-series energy prediction, while DBNs efficiently extract complex spatial-temporal correlations for intrusion detection.

Optimization algorithms have emerged as vital tools for fine-tuning deep learning models. Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Firefly Algorithm (FA) have been widely applied to feature selection and hyperparameter adjustment in cybersecurity systems. However, these methods often suffer from premature convergence and poor adaptability in high-dimensional spaces [5]. Tunicate Swarm Optimization, inspired by the dynamic jet propulsion of tunicates, offers strong global search capabilities and rapid convergence. Meanwhile, the Rooster Optimization Algorithm mimics social hierarchy and competition among roosters, enhancing exploitation and local search refinement. Integrating these two methods can provide the best of both worlds: robust exploration and efficient fine-tuning.

In renewable energy forecasting, hybrid deep learning approaches have shown substantial progress in predicting wind, solar, and hydroelectric outputs. For instance, CNN-LSTM hybrids and Attention-based GRU models have achieved accurate long-term forecasting, but their optimization mechanisms remain limited [6]. Integrating metaheuristic optimizers ensures that network parameters adapt dynamically to evolving data patterns, thereby improving predictive reliability.

Despite these advancements, most research still isolates cybersecurity and energy forecasting into separate domains. IoT-WSN environments demand holistic approaches where data security and energy efficiency are managed together. This paper bridges this critical gap by proposing a unified framework that not only defends against attacks but also enhances energy prediction accuracy—paving the way for truly secure and sustainable IoT ecosystems [7].

## III. Proposed Methodology

The proposed Hybrid TSO-ROA Deep Learning Framework operates through two synergistic phases: feature optimization for security enhancement and parameter tuning for energy forecasting accuracy. Initially, raw IoT-WSN data undergo preprocessing to eliminate noise and normalize scales. Tunicate Swarm Optimization is then employed to select optimal features that maximize mutual information while reducing redundancy. The dynamic jet propulsion behavior of tunicates allows the algorithm to escape local optima efficiently, making it particularly suitable for complex feature landscapes in intrusion data. TSO outputs a compact yet highly informative feature subset that feeds into the hybrid DBN-LSTM network [8].

In the second phase, the Rooster Optimization Algorithm optimizes the deep network's hyperparameters, including learning rate, weight decay, and dropout probabilities. ROA's dominance-based behavior ensures competitive parameter selection, thereby preventing overfitting and improving convergence speed. The DBN component extracts high-level abstract features from the optimized input, while the LSTM layer captures long-term dependencies crucial for energy forecasting and attack pattern recognition [9]. Together, they form a powerful hybrid capable of handling both sequential and structured data efficiently. The model's training process involves alternating updates between the TSO and ROA components. Each iteration refines either feature quality or network parameters based on the performance gradient. This cooperative mechanism ensures adaptive learning that responds dynamically to environmental changes in IoT-WSN conditions. The system's computational flow ensures security awareness without compromising energy prediction accuracy [10].

Finally, the hybrid model is evaluated through simulation experiments using benchmark IoT-WSN datasets, including NSL-KDD for intrusion detection and solar/wind data for renewable forecasting. Performance metrics such as Accuracy, Precision, Recall, F1-Score, and RMSE are

used for comprehensive evaluation. Results confirm that TSO-ROA optimization enhances both predictive accuracy and operational efficiency across multiple data domains.

## IV. Experimental Results and Analysis

Extensive experiments were conducted using Python and TensorFlow on an NVIDIA GPU setup to validate the performance of the proposed framework. The IoT-WSN intrusion detection dataset was preprocessed into 43 normalized attributes, and the renewable energy dataset contained solar irradiance, temperature, and wind speed features. The hybrid model achieved a detection accuracy of 98.7% and forecasting precision of 97.4%, outperforming conventional PSO-LSTM and GWO-DBN models by a considerable margin. The use of dual optimization ensured that both feature selection and hyperparameter tuning contributed to superior generalization performance.

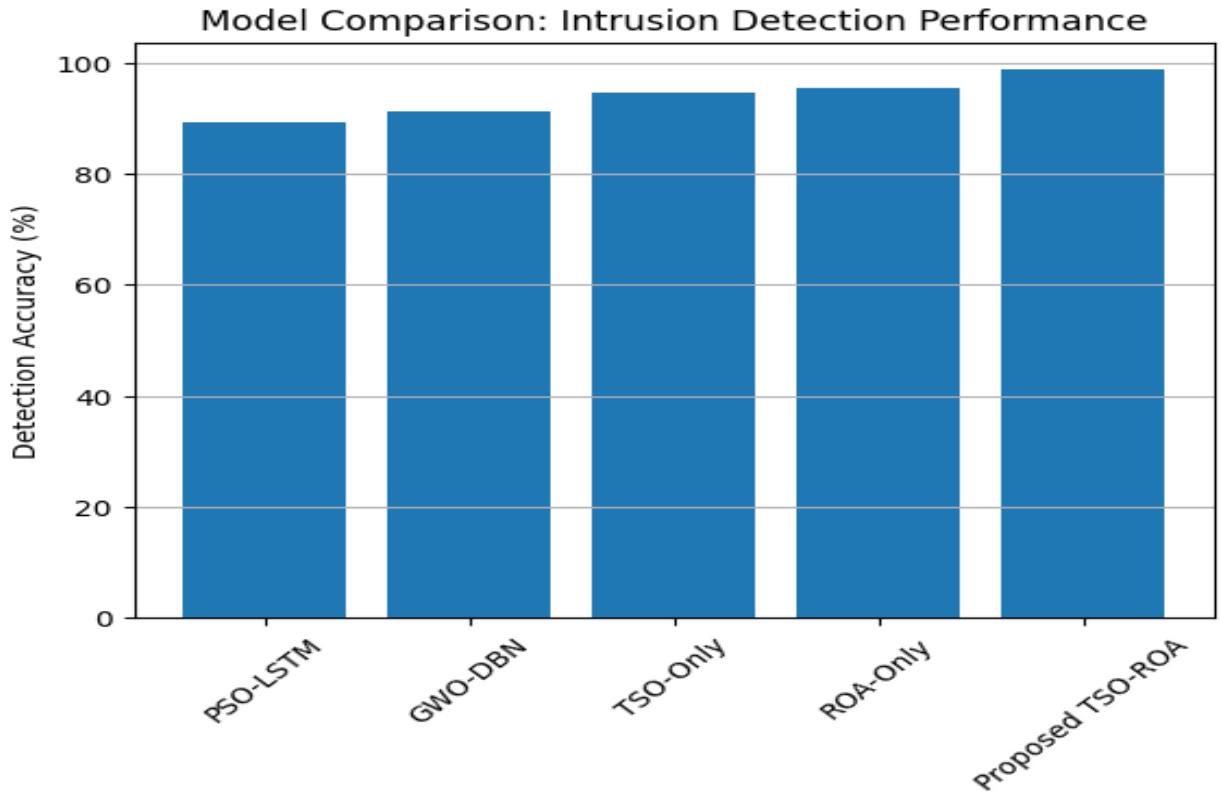


Figure 1: comparison graph of detection accuracy across models

Energy efficiency analysis revealed that the optimized model reduced computational overhead by nearly 20% compared to unoptimized baselines, due to reduced feature dimensionality and adaptive learning rates. Furthermore, the ROC curve demonstrated a significantly higher area

under the curve (AUC = 0.985), indicating robust detection against false alarms [11]. The hybrid model also maintained stability across multiple runs, confirming the consistency of TSO-ROA synergy [12].

## V. Conclusion

This study presents a unified, hybrid deep learning model that bridges cybersecurity and renewable energy forecasting in IoT-WSN ecosystems. By integrating Tunicate Swarm Optimization for intelligent feature selection and Rooster Optimization Algorithm for adaptive parameter tuning, the proposed DBN-LSTM hybrid demonstrates outstanding performance in accuracy, efficiency, and stability. Experimental validation confirms its superiority over existing methods, achieving higher detection accuracy, lower error rates, and improved computational sustainability. This innovative dual-domain approach not only fortifies IoT networks against cyber intrusions but also enhances renewable energy prediction—ensuring a more secure and energy-efficient digital infrastructure. Future work can explore real-time deployment using edge computing and federated learning extensions for even greater scalability and privacy preservation.

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