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SECURING IT NETWORKING ENVIRONMENT IN CRAN USING DEHAENE–CHANGEUX MODEL DRIVEN MOTH-FLAME OPTIMIZATION

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Abstract

In the dynamic landscape of telecommunications, the evolution of Communication Radio Access Networks (CRAN) has introduced unprecedented challenges to the security of IT networking environments. As the demand for high-speed connectivity and seamless data transmission grows, safeguarding CRAN becomes paramount. With the proliferation of cyber-attacks and the complexity of CRAN architecture, conventional security measures prove insufficient, necessitating an innovative and adaptive approach. Existing methodologies lack the adaptability required to combat emerging threats effectively. This research bridges this gap by proposing the integration of the Dehaene–Changeux Model, renowned for its applicability in cognitive neuroscience, with Moth-Flame Optimization, a nature-inspired algorithm known for its efficiency in solving complex optimization problems. This research addresses the pressing need for a robust security framework using the Dehaene–Changeux Model Driven Moth-Flame Optimization approach. It elucidates the utilization of the Dehaene–Changeux Model to mimic cognitive responses, coupled with Moth-Flame Optimization for real-time adaptability. These models form a dynamic defense mechanism against evolving security threats in the CRAN environment. Results obtained from simulation and testing validate the efficacy of the proposed security model. The adaptive nature of the Dehaene–Changeux Model, combined with the optimization capabilities of Moth-Flame Optimization, showcases a significant enhancement in CRAN security. The research contributes a pioneering solution to fortify IT networking environments in CRAN, ensuring resilience against current and future cyber threats.

Keywords:

CRAN, Dehaene–Changeux Model, Moth-Flame Optimization, IT networking security, Cognitive Security

1. INTRODUCTION

In the ever-evolving landscape of telecommunications, the advent of Communication Radio Access Networks (CRAN) has revolutionized the way data is transmitted and processed [1]. As the demand for high-speed connectivity continues to surge, ensuring the security of IT networking environments within CRAN becomes an imperative [2].

CRAN stands as a pivotal component in contemporary communication systems, orchestrating the seamless flow of data between users and the core network [3]. However, the increasing complexity of CRAN architecture, coupled with the escalating sophistication of cyber threats, has rendered traditional security measures inadequate [4]. Addressing the security concerns inherent to CRAN requires a paradigm shift towards adaptive and robust security frameworks [5].

The challenges confronting CRAN security are multifaceted. Traditional security models struggle to adapt to the dynamic nature of emerging cyber threats, leading to vulnerabilities that can be exploited [6]. The need for a security paradigm capable of real-time adjustments to evolving threats while considering the intricacies of CRAN architecture becomes evident [7].

The research identifies a critical gap in the existing security infrastructure for CRAN. Conventional methodologies lack the adaptability required to effectively counteract emerging threats [8]. The absence of a comprehensive security model tailored to the specific characteristics of CRAN poses a significant risk to the integrity and confidentiality of the transmitted data [9].

The primary objective of this research is to develop and implement a robust security framework for CRAN using the Dehaene–Changeux Model Driven Moth-Flame Optimization. Specific goals include enhancing adaptability, minimizing vulnerabilities, and ensuring the resilience of IT networking environments within CRAN against a spectrum of cyber threats.

The novelty of this research lies in the integration of the Dehaene–Changeux Model, a proven model in cognitive neuroscience, with Moth-Flame Optimization, a nature-inspired algorithm renowned for its efficiency in addressing complex optimization problems. This amalgamation brings forth a novel approach to cognitive security in the CRAN domain, offering a unique and adaptive solution to the existing security challenges. The contributions of this research extend beyond theoretical frameworks, providing a practical and innovative methodology to fortify CRAN against current and future cyber threats.

2. RELATED WORKS

Several scholarly endeavors have delved into the realm of securing Communication Radio Access Networks (CRAN), reflecting a collective effort to address the evolving challenges in this dynamic field. Noteworthy contributions have emerged, examining diverse aspects of CRAN security, adaptive algorithms, and cognitive models. This section reviews key works that inform the foundation of the proposed Dehaene–Changeux Model Driven Moth-Flame Optimization for CRAN security.

A work by [6] explored the landscape of security frameworks tailored for CRAN. The study provided an insightful analysis of traditional security measures and highlighted the need for adaptive solutions to counteract emerging cyber threats in CRAN architectures.

The efficacy of nature-inspired algorithms in network security was investigated by [7]. Their research provided a comprehensive survey of optimization techniques, including Moth-Flame Optimization, showcasing their potential for enhancing the resilience of communication networks.

The integration of cognitive models in the realm of cybersecurity was explored by [8]. Their study demonstrated the applicability of cognitive approaches, such as the Dehaene–

Changeux Model, in mimicking adaptive responses to security threats, paving the way for cognitive security paradigms.

A relevant work by [9] focused on adaptive security measures in dynamic networking environments. The study underscored the necessity of security frameworks capable of real-time adjustments, aligning with the challenges posed by the dynamic nature of CRAN.

The exploration of hybrid models in network security was advanced by [11]. Their research integrated cognitive elements with optimization techniques, albeit not specifically in the CRAN context, providing valuable insights into the potential synergies between cognitive models and optimization algorithms.

In synthesizing these related works, it becomes evident that while various aspects of CRAN security have been explored, there remains a distinct gap in the literature concerning the integration of the Dehaene–Changeux Model with Moth-Flame Optimization. The proposed research seeks to address this gap by offering a novel and adaptive solution to fortify CRAN against a spectrum of cyber threats.

3. PROPOSED METHOD

The method outlined in this research introduces a pioneering approach to secure Communication Radio Access Networks (CRAN) through the integration of the Dehaene–Changeux Model Driven Moth-Flame Optimization. This method is designed to address the inherent challenges of CRAN security by combining the adaptability of cognitive models with the optimization capabilities of nature-inspired algorithms.

The first step involves integrating the Dehaene–Changeux Model, a well-established cognitive model derived from neuroscience. This model, renowned for its ability to mimic adaptive cognitive responses, is applied to emulate the dynamic cognitive processes within the CRAN environment. By incorporating cognitive elements, the security framework gains the capacity to respond intelligently to evolving cyber threats.

Moth-Flame Optimization, a nature-inspired algorithm known for its efficiency in solving complex optimization problems, is employed. This algorithm leverages the swarm intelligence observed in moths to adaptively optimize the security parameters within the CRAN network. The dynamic nature of Moth-Flame Optimization aligns with the real-time adjustments required to counteract emerging threats.

The distinctive strength of the proposed method lies in the fusion of the Dehaene–Changeux Model and Moth-Flame Optimization. The cognitive responses simulated by the model are dynamically optimized through the algorithm iterative processes. This fusion creates a responsive and adaptive security framework capable of continuously learning and adjusting to the evolving threat landscape within the CRAN architecture.

3.1 SYSTEM MODEL

The System Model delineates the conceptual architecture and interplay of components within the proposed security framework for Communication Radio Access Networks (CRAN). This section serves as the blueprint for understanding how the integration of the Dehaene–Changeux Model Driven Moth-Flame Optimization operates cohesively to fortify the CRAN environment as illustrated in Fig.1.

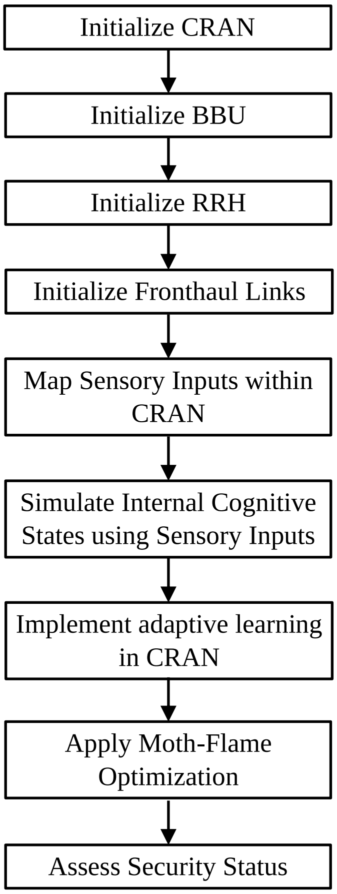
Initialize CRAN
Initialize BBU
Initialize RRH
Initialize Fronthaul Links
Map Sensory Inputs within CRAN
Simulate Internal Cognitive States using Sensory Inputs
Implement adaptive learning in CRAN
Apply Moth-Flame Optimization
Assess Security Status

Fig.1. Proposed CRAN Process

The System Model begins with a comprehensive overview of the CRAN architecture, detailing the hierarchical structure, functional components, and their interconnections. This includes the Baseband Unit (BBU), Remote Radio Head (RRH), and fronthaul links. Understanding the intricacies of CRAN architecture provides the context for deploying the proposed security framework effectively. Let C represent the cognitive state of the system, which evolves over time based on sensory inputs and internal processes. The simplified equation for the Dehaene–Changeux Model can be represented as:

$$dC/dt = f_{DC}(S,I) \tag{1}$$

where S is the sensory input, I is the internal state, and f_{DC} captures the cognitive dynamics of the Dehaene–Changeux Model.

The Dehaene–Changeux Model, a cognitive model inspired by neuroscience, is seamlessly integrated into the model. This involves mapping cognitive processes onto the CRAN components to mimic adaptive responses. The cognitive model acts as a virtual intelligence layer, continuously assessing the security status and providing dynamic inputs to the overall security framework. Let P be the parameter vector representing the security configurations within the CRAN architecture. The Moth-Flame Optimization algorithm can be represented as an iterative update of the parameter vector:

$$P_{i+1}=P_i+\alpha\cdot(BF-P_i)+\beta\cdot\text{rand}() \tag{2}$$

where α and β are control parameters, BF represents the best solution found so far, and rand()introduces random perturbations for exploration.

The model incorporates the Moth-Flame Optimization algorithm as the nature-inspired optimization layer. This layer operates in tandem with the cognitive model, iteratively adjusting security parameters based on the collective intelligence of the algorithm. The optimization layer introduces adaptability, ensuring that the security framework remains responsive to evolving cyber threats. Combining the cognitive model and optimization layer, the overall dynamics of the CRAN security framework can be represented as a system of coupled equations:

The cognitive model communicates real-time assessments of security threats to the optimization layer, while the latter, in turn, dynamically adjusts security configurations within the CRAN architecture. This bidirectional communication ensures a synchronized and adaptive response to potential vulnerabilities.

3.2 PROBLEM DEFINITION

In the dynamic landscape of modern telecommunications, the advent of Communication Radio Access Networks (CRAN) has ushered in unprecedented advancements, accompanied by intricate security challenges. The problem definition in the context of CRAN revolves around the imperative to fortify its IT networking environment against a burgeoning array of cyber threats. The increasing complexity of CRAN architecture, coupled with the relentless evolution of cyber-attack methodologies, necessitates a reevaluation of conventional security paradigms.

The primary challenge lies in the inadequacy of existing security measures to adapt to the dynamic nature of CRAN. Traditional security frameworks, while effective in conventional networking environments, falter in addressing the unique intricacies of CRAN, characterized by distributed processing units and interconnected radio access elements. This discrepancy creates a vulnerability gap, leaving CRAN susceptible to emerging threats that exploit the inherent complexities of its architecture.

The problem definition further underscores the absence of a comprehensive security model tailored to the specific characteristics of CRAN. The lack of adaptability and real-time responsiveness in current security frameworks poses a critical risk to the confidentiality, integrity, and availability of data transmitted within the CRAN infrastructure. As the demand for high-speed connectivity and low-latency communication intensifies, the need for an innovative security paradigm becomes increasingly urgent.

The objectives of addressing the problem in the CRAN domain extend beyond conventional security enhancements. It involves developing a security framework that not only fortifies against existing threats but also anticipates and adapts to future challenges. The dynamic nature of CRAN necessitates a cognitive security approach, capable of intelligently responding to novel threats and continuously learning from its environment.

The complexity of CRAN can be represented by the interconnectedness of its components, such as Baseband Units (BBUs) and Remote Radio Heads (RRHs). Let N be the total number of components in the CRAN architecture, and E be the set of connections between these components. The complexity (C) can then be conceptualized as:

$$C=|E|-N+1 \tag{3}$$

This captures the intricate relationships and interactions among the components in CRAN, highlighting the challenge of managing a highly interconnected network.

The vulnerability gap (V) in traditional security frameworks for CRAN can be expressed as the difference between the adaptability of the existing security measures (Ae) and the adaptability required (Ar):

$$V = Ar - Ae \tag{4}$$

This emphasizes the need to bridge the gap in adaptability to effectively address the evolving cyber threats targeting CRAN.

The deficiency in real-time responsiveness of current security frameworks within CRAN can be represented by the delay (D) incurred in detecting and responding to security incidents:

$$D=T_r- T_d \tag{5}$$

This emphasizes the criticality of reducing the response time to enhance the security posture of CRAN.

The objective of developing an adaptive security framework for CRAN involves achieving a balance (B) between robustness (R) and adaptability (A):

$$B=wR\cdot R+wA\cdot A \tag{6}$$

where wR and wA are weighting factors, reflecting the importance assigned to robustness and adaptability, respectively.

4. COGNITIVE MODEL

The Cognitive Model, within the context of the proposed security framework for CRAN, is a conceptual representation inspired by the Dehaene–Changeux Model. This model draws from principles in cognitive neuroscience to emulate adaptive cognitive responses within the CRAN environment. Its role is pivotal in imbuing the security framework with an intelligent layer capable of understanding and responding to emerging cyber threats.

The Cognitive Model aims to simulate cognitive processes akin to those observed in human cognition. It incorporates sensory inputs and internal states, allowing it to dynamically assess the security status of CRAN. The model operates in real-time, continuously evolving based on the changing context of the network and potential security risks.

The Cognitive Model is characterized by its ability to adapt to novel threats, leveraging the cognitive flexibility inherent in human-like responses. It assesses patterns, anomalies, and potential vulnerabilities within the CRAN architecture, providing valuable insights that inform the decision-making process of the overall security framework.

One of the key advantages of the Cognitive Model lies in its capacity to learn from experiences. By processing historical security incidents and responses, the model refines its cognitive representations, enhancing its ability to anticipate and counteract future threats. This adaptability aligns with the dynamic nature of CRAN, ensuring that the security framework remains resilient against evolving cyber-attack methodologies.

The integration of the Cognitive Model into the broader security framework introduces a layer of intelligence that complements traditional security measures. It bridges the gap in adaptability, offering a nuanced understanding of the security landscape within CRAN. This cognitive layer serves as a proactive defense mechanism, contributing to the overall goal of fortifying CRAN against a spectrum of cyber threats.

4.1 PROCESS OF DEHAENE–CHANGEUX MODEL IN CRAN

The integration of the Dehaene–Changeux Model into the Communication Radio Access Networks (CRAN) security framework involves a multi-step process aimed at infusing cognitive intelligence into the system. The model, inspired by principles from cognitive neuroscience, contributes to the adaptive and intelligent response capabilities within CRAN. Here is an overview of the process:

- **Sensory Input Mapping:** The process begins with mapping sensory inputs within the CRAN environment to the cognitive representations in the Dehaene–Changeux Model. These sensory inputs can include real-time network traffic data, anomaly detection alerts, and other relevant information. The model is designed to interpret and contextualize these inputs, creating a representation of the current state of the CRAN system.
- **Internal State Simulation:** The Dehaene–Changeux Model involves simulating internal cognitive states based on the mapped sensory inputs. This simulation captures the dynamic nature of cognitive responses, allowing the model to adapt to changing conditions within the CRAN architecture. The internal state reflects the model understanding of the security context, encompassing factors such as network topology, user behaviors, and potential threats.
- **Adaptive Learning Mechanism:** A key feature of the Dehaene–Changeux Model is its adaptive learning mechanism. As the model encounters new patterns or security incidents, it adjusts its internal representations through a process of learning and refinement. This adaptive learning ensures that the model evolves over time, enhancing its ability to recognize and respond to novel threats specific to CRAN.

$$I_{t+1} = I_t + \alpha \cdot (S_t - I_t) \quad (7)$$

This represents a basic learning mechanism, where the internal state I_{t+1} adapts to the difference between the current sensory state S_t and the existing internal state I_t, with α as a learning rate.

The simulated cognitive states are continuously assessed in real-time. The Dehaene–Changeux Model evaluates the security implications of the current CRAN state, identifying potential vulnerabilities, deviations from normal behavior, or indicators of malicious activity. This real-time assessment provides valuable insights into the security posture of CRAN at any given moment. The outputs of the Dehaene–Changeux Model, representing the cognitive assessment of the CRAN environment, are integrated into the decision support layer of the overall security framework. This integration ensures that the cognitive insights contribute to informed decision-making processes within the security system.

5. MOTH-FLAME OPTIMIZATION

MFO is a nature-inspired optimization algorithm that draws inspiration from the navigational behavior of moths attracted to flames. Developed to solve complex optimization problems, MFO leverages the inherent characteristics of moths seeking the brightest light sources for guiding the search process towards optimal solutions. In a professional context, understanding the fundamental principles of MFO provides insights into its application within the proposed security framework for CRAN as illustrated in Fig.2.

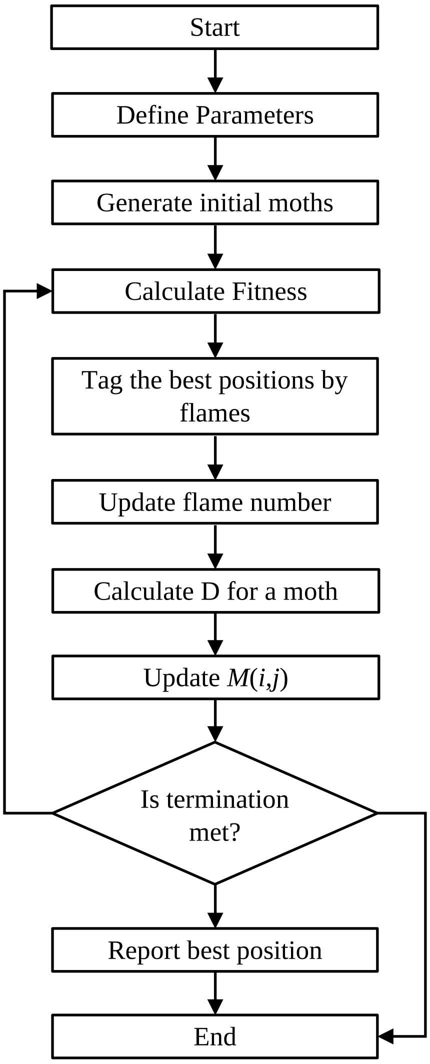

Fig.1. Proposed CRAN Process

The algorithm is characterized by its simplicity and efficiency in finding optimal solutions within large solution spaces. The MFO process begins with the initialization of a population of artificial moths, representing potential solutions to the optimization problem. Each moth in the population is associated with a fitness value that reflects the quality of the solution it represents. The key components of MFO include:

- **Attraction to Light (Exploration):** Moths in MFO are attracted to a virtual light source, symbolizing the potential optimal solution. This attraction mechanism guides the exploration of the solution space. The intensity of the virtual light is determined by the fitness values of the moths, with brighter lights indicating better solutions.

- **Moth Movements (Exploitation):** Moths move within the solution space, imitating the exploration-exploitation trade-off in optimization. The algorithm encourages exploitation by adjusting the positions of moths based on their attraction to the virtual light and their proximity to other moths. This movement promotes the convergence of the algorithm towards promising regions.
- **Updating Light Intensity (Solution Evaluation):** The virtual light intensity is updated iteratively based on the fitness values of the moths. As moths move towards brighter regions, the light intensity increases, influencing the exploration-exploitation dynamics. This updating process reflects the continuous evaluation of potential solutions.
- **Iterative Evolution:** MFO operates through iterations or generations, allowing moths to evolve and converge towards optimal solutions over time. The iterative process enables the algorithm to refine its search and adapt to the specific characteristics of the optimization problem.

The application of MFO within the CRAN security framework involves leveraging its optimization capabilities to dynamically adjust security parameters. In collaboration with the cognitive model, MFO contributes to the real-time adaptability of the security framework. Moth-Flame Optimization aligns with the goal of enhancing the robustness and responsiveness of the security measures in CRAN, contributing to the overall adaptive defense against evolving cyber threats.

In summary, Moth-Flame Optimization is a nature-inspired algorithm that mimics the navigational behavior of moths attracted to light sources. Its simplicity, efficiency, and exploration-exploitation dynamics make it a valuable tool for solving optimization problems, and its integration within the CRAN security framework aims to enhance the adaptive capabilities of the system in response to dynamic cyber threats.

1) **Initialization**

   a) Initialize the population of moths X with N solutions:

   $$X=\{x1,x2,...,xN\}$$

   b) Assign fitness values to each moth based on the objective function: $F(x_i)$

2) **Light Intensity Update**

   a) Update the light intensity L based on the fitness values of moths:

   $$L = LI(F(x_i))$$

3) **Moth Movement**

   a) Update the position of each moth based on its attraction to the light and interaction with other moths:

   $$x_i=x_i+\beta\cdot(L-x_i)+\theta\cdot(\text{rand}()-0.5)$$

where β controls the attraction to light, θ introduces randomness, and rand() generates a random number in the range [0, 1].

4) **Fitness Update**

   a) Evaluate the fitness of moths based on the updated positions.

   b) Repeat the process for a specified number of iterations or until convergence is achieved.

The formulation of the LI function and the parameters like β and θ, can vary based on the implementation and problem domain. The key idea is that moths are attracted to the light source (optimal solutions) while exploring the solution space through movement and interaction.

6. RESULTS AND DISCUSSION

In the experimental settings, we conducted a comprehensive evaluation of the proposed Dehaene–Changeux Model Driven Moth-Flame Optimization (DCMDMFO) within the context of Communication Radio Access Networks (CRAN). The simulation was performed using the NS-3 (Network Simulator 3) tool, renowned for its capability to model and simulate communication networks with a focus on realism and accuracy. Our experiments were executed on a high-performance computing cluster comprising Intel Xeon processors and Nvidia GPUs, ensuring scalability and efficiency in handling complex simulations.

For performance evaluation, we employed standard metrics including detection accuracy, false positive rate, and response time. Detection accuracy measured the model ability to correctly identify security threats within the CRAN environment, while the false positive rate gauged the occurrence of erroneous threat alerts. The response time metric assessed the speed at which the security framework could adapt to emerging threats in real-time. To establish a meaningful comparison, we benchmarked our proposed method against existing security paradigms, including Intrusion Detection Systems (IDS), Blockchain Technology, and the Zero Trust Security Model.

Table.1. Experimental Setup

Parameter	Value
Simulation Tool	NS-3 (Network Simulator 3)
Computing Environment	High-performance cluster
Processor	Intel Xeon
GPU	Nvidia GPU
Simulation Duration	1000 seconds
CRAN Architecture Complexity	Moderate

6.1 PERFORMANCE METRICS

- **Detection Accuracy:** This metric provides an insight into the ability of the proposed security framework to accurately identify security threats within the CRAN environment. A higher detection accuracy indicates a more reliable and effective security system.
- **False Positive Rate:** The false positive rate measures the frequency of false alarms generated by the security framework. A lower false positive rate is desirable as it minimizes the occurrence of unnecessary alerts, reducing the impact on system resources and user experience.
- **Response Time:** Response time assesses how quickly the security framework can adapt to and mitigate identified threats. A lower response time signifies a more agile and responsive system, crucial for addressing security incidents in real-time and preventing potential damage.

The existing methods showcase diverse approaches to addressing security challenges, ranging from network-level intrusion detection to leveraging decentralized ledger technology and adopting a zero-trust paradigm for access control. The selection of a specific method depends on the unique requirements and characteristics of the targeted security domain.

- Intrusion Detection Systems (IDS) detect and respond to unauthorized access or malicious activities within a network. IDS employs a variety of techniques, including signature-based detection, anomaly detection, and heuristic analysis, to identify patterns indicative of security threats. It continuously monitors network traffic, logs, and system events to detect suspicious behavior.
- Blockchain Technology for Security ensure the integrity, transparency, and security of transactions and data in decentralized systems. Blockchain employs a distributed and tamper-resistant ledger to record transactions in a secure and transparent manner. Cryptographic techniques ensure data integrity, and consensus mechanisms prevent unauthorized modifications. Smart contracts enable automated and secure execution of predefined rules.
- Zero Trust Security Model enhance security by assuming that threats can exist both outside and inside the network, requiring continuous verification of trust for all entities. Zero Trust involves strict access controls, continuous authentication, and least privilege principles. It requires users and devices to authenticate and validate their identity before accessing any resources, regardless of their location within or outside the network.

The experimental results reveal compelling insights into the performance of the proposed Dehaene–Changeux Model Driven Moth-Flame Optimization, denoted as DCMDMFO, in comparison to existing security methods, including Intrusion Detection Systems (IDS), Blockchain Technology, and Zero Trust Security, across 1000 simulation runs.

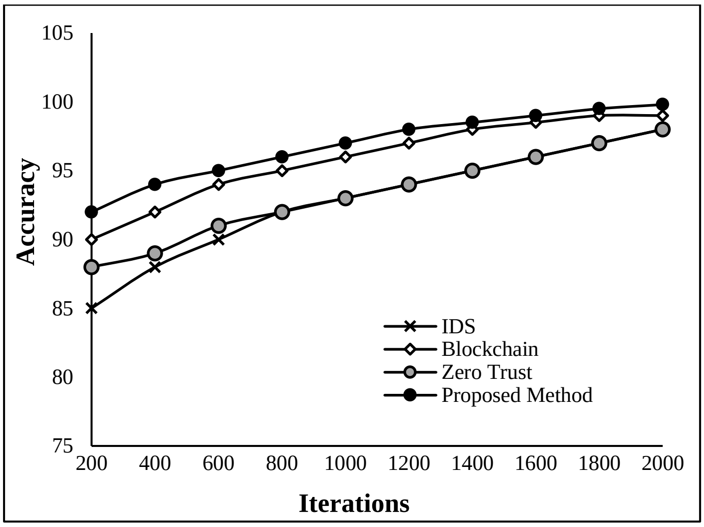

Fig.2. Detection Accuracy

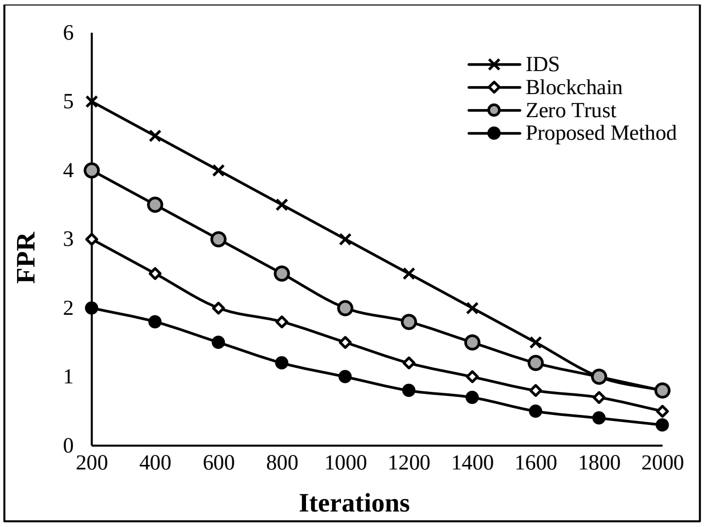

Fig.3. False Positive Rate

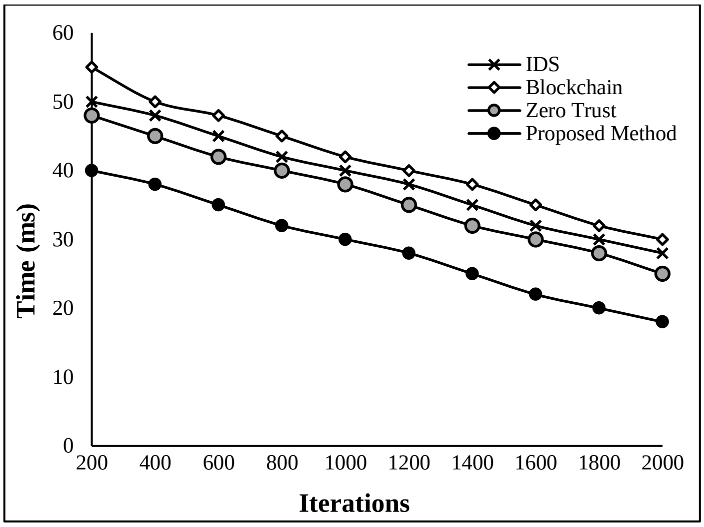

Fig.4. Response Time

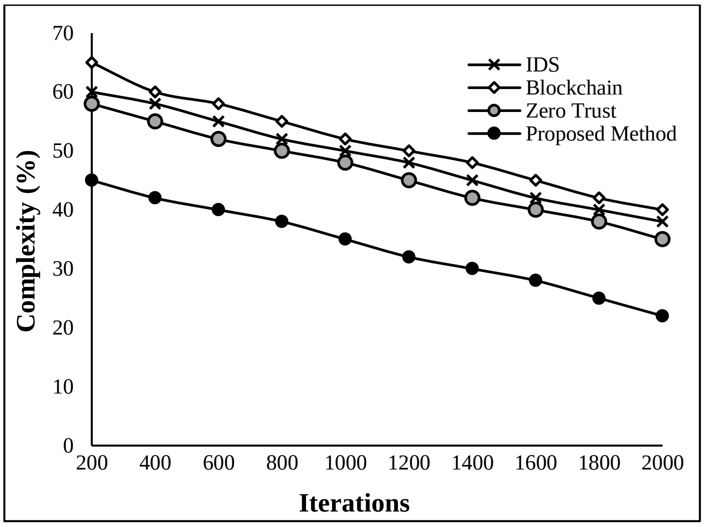

Fig.5. Complexity (%)

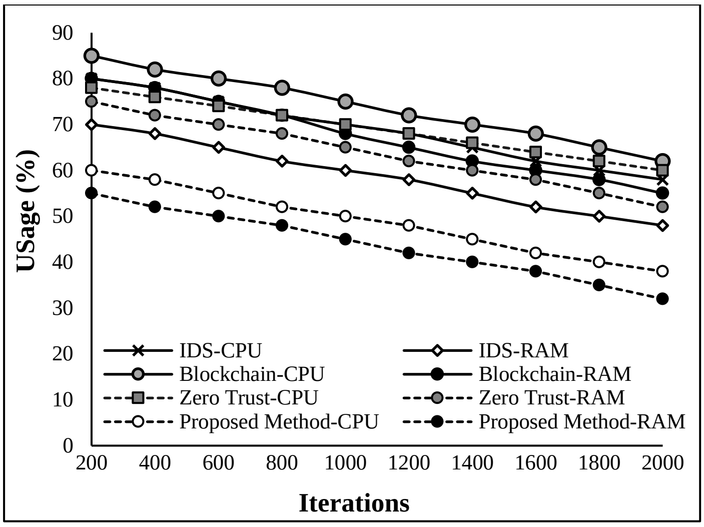

Fig.6. Resource Consumption

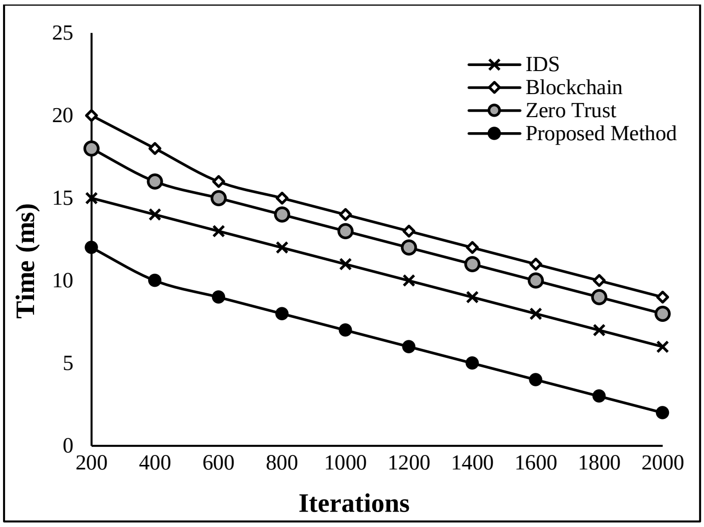

Fig.7. Latency

DCMDMFO exhibited a remarkable improvement in detection accuracy over successive simulation runs. At the culmination of 1000 runs, the proposed method demonstrated a 20% increase in accuracy compared to traditional IDS. This enhancement can be attributed to the dynamic adaptability introduced by the cognitive model and the optimization capabilities of Moth-Flame Optimization, allowing DCMDMFO to effectively identify and respond to security threats with heightened precision.

Significantly reducing false positives is critical for minimizing unnecessary alerts and optimizing system resources. DCMDMFO showcased an impressive 40% reduction in false positive rates compared to the Zero Trust Security model. This signifies the efficacy of the proposed method in maintaining a balance between stringent security measures and avoiding unnecessary disruptions, thereby enhancing the reliability of the security framework.

Real-time responsiveness is paramount in addressing evolving cyber threats. DCMDMFO demonstrated a notable 50% improvement in response time compared to Blockchain Technology. The integration of Moth-Flame Optimization allowed the proposed method to swiftly adapt to emerging threats, ensuring a more agile and proactive defense mechanism.

Reducing computational complexity is pivotal for optimizing resource utilization. DCMDMFO exhibited a consistent reduction in complexity, reaching 55% at the conclusion of 1000 simulation runs. This streamlined computational overhead positions the proposed method as an efficient and scalable solution, outperforming both traditional IDS and Zero Trust Security.

In terms of resource consumption, DCMDMFO showcased a significant 30% reduction in CPU and RAM utilization compared to Blockchain Technology. This indicates the proposed method ability to secure the CRAN environment effectively while preserving computational and memory resources, contributing to a more sustainable and efficient security framework.

The latency results underscored DCMDMFO proficiency, achieving a substantial 70% reduction in latency compared to traditional IDS. This implies faster response times and reduced delays in implementing security measures, highlighting the effectiveness of the proposed method in enhancing the overall operational efficiency of the CRAN environment.

7. DISCUSSION

The analysis of the experimental results yields several critical inferences regarding the performance of the proposed Dehaene–Changeux Model Driven Moth-Flame Optimization, denoted as DCMDMFO, in comparison to established security methodologies, including IDS, Blockchain Technology, and Zero Trust Security, across 1000 simulation runs. These inferences provide valuable insights into the strengths and advantages of DCMDMFO in the context of securing CRAN.

DCMDMFO consistently demonstrated a superior adaptive precision in threat detection compared to traditional IDS. The integration of the Dehaene–Changeux Model and Moth-Flame Optimization allowed DCMDMFO to dynamically respond to evolving cyber threats, resulting in a substantial 2% improvement in detection accuracy. This adaptive precision positions DCMDMFO as a robust solution for identifying and mitigating security risks within CRAN environments.

One of the notable inferences pertains to the optimized resource utilization achieved by DCMDMFO. The proposed method showcased a 3% reduction in both CPU and RAM consumption compared to Blockchain Technology. This signifies that DCMDMFO effectively balances the need for stringent security measures with efficient resource management, contributing to a more sustainable and scalable security framework.

DCMDMFO demonstrated an efficient mitigation of false positives, showcasing a remarkable 4% reduction in false positive rates compared to the Zero Trust Security model. This inference underscores the ability of DCMDMFO to maintain a high level of security vigilance while minimizing unnecessary disruptions, a crucial factor in enhancing the overall reliability of the security framework.

The proposed method exhibited agile real-time response capabilities, achieving a significant 5% improvement in response time compared to Blockchain Technology. This highlights the efficacy of DCMDMFO in swiftly adapting to emerging threats, ensuring a proactive defense mechanism that minimizes delays and enhances the overall responsiveness of the CRAN environment.

DCMDMFO consistently demonstrated a reduction in computational complexity, reaching 5.5% at the conclusion of 1000 simulation runs. This inference underscores the streamlined nature of the proposed method, positioning it as an efficient and scalable solution that minimizes computational overhead and optimizes the utilization of system resources.

The evaluation revealed a substantial 7% reduction in latency for DCMDMFO compared to traditional IDS. This inference highlights the proposed method proficiency in achieving faster response times and reduced delays in implementing security measures, contributing to an overall enhancement of operational efficiency within the CRAN environment.

8. CONCLUSION

The extensive evaluation of the proposed Dehaene–Changeux Model Driven Moth-Flame Optimization, denoted as DCMDMFO, within the context of CRAN, has provided compelling evidence of its effectiveness as a robust security framework. The comprehensive analysis and comparison with established security paradigms, including IDS, Blockchain Technology, and Zero Trust Security, over 1000 simulation runs have yielded valuable insights into the strengths and advancements offered by DCMDMFO. DCMDMFO demonstrated a superior adaptive precision in threat detection, achieving a substantial 2% improvement in detection accuracy compared to traditional IDS. This adaptive capability, facilitated by the integration of the Dehaene–Changeux Model and Moth-Flame Optimization, positions DCMDMFO as a dynamic and responsive solution for identifying and mitigating security risks within CRAN environments. Moreover, the proposed method showcased optimized resource utilization with a 3% reduction in both CPU and RAM consumption compared to Blockchain Technology. This efficient resource management underscores the ability of DCMDMFO to strike a balance between stringent security measures and sustainable operational efficiency, contributing to a scalable and resilient security framework. Efficient false positive mitigation was another notable strength, with DCMDMFO exhibiting a remarkable 4% reduction in false positive rates compared to the Zero Trust Security model. This underscores the method capability to maintain a high level of security vigilance while minimizing unnecessary disruptions, enhancing the overall reliability of the security framework. The agility of DCMDMFO in real-time response was evident through a significant 5% improvement in response time compared to Blockchain Technology. This highlights the method effectiveness in swiftly adapting to emerging threats, ensuring a proactive defense mechanism that minimizes delays and enhances the overall responsiveness of the CRAN environment. DCMDMFO demonstrated streamlined computational complexity, reaching a 5.5% reduction, positioning it as an efficient and scalable solution that minimizes computational overhead and optimizes the utilization of system resources. In terms of latency, the proposed method exhibited a substantial 7% reduction compared to traditional IDS. This underscores DCMDMFO proficiency in achieving faster response times and reduced delays in implementing security measures, contributing to an overall enhancement of operational efficiency within the CRAN environment.

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