

Development of a Chaotic Tent Map-Enhanced Pelican Optimization Algorithm for Artificial Neural Network-Based Intrusion Detection in Mobile Ad Hoc Networks

Olanrewaju S. S.¹, Ayeni J. A.², Oyediran M. O.³

¹Department of Science Education, Federal College of Edu. (Sp.) Oyo, Nigeria.

^{2,3}Department of Computer Science, Ajayi Crowther University Oyo, Nigeria.

ARTICLE INFO	ABSTRACT
Published Online: 03 September 2026	Mobile Ad hoc Networks are self-organising, infrastructure-less networks with dynamic topologies. These characteristics provide flexibility in network deployment but also make the network highly susceptible to serious security threats such as blackhole, sybil and wormhole attacks that can affect network performance. Standard ANN has been identified as a strong intrusion detection technique once the best hyperparameters were selected also standard optimization algorithms often suffer from premature convergence during optimization process, this study introduces a Chaotic Tent Map-Enhanced Pelican Optimization Algorithm-Artificial Neural Network (CTM-POA-ANN) framework to improve intrusion detection performance through efficient ANN hyperparameter optimization. The proposed methodology intends to improve population diversity, global exploration and effective fine-tuning of ANN hyperparameters using enhanced pelican optimization algorithm, the CTM-POA-ANN technique is tested using network traffic generated in the NS-3 simulation under normal communication and multiple attack scenarios. The experimental results depict that the proposed CTM-POA-ANN framework achieved 95.93% precision, 95.84% recall, accuracy of 95.85% and F1-score of 95.77% which outperforms traditional ANN and POA-ANN paradigms significantly. The findings indicate that the integration of Chaotic Tent Map with the Pelican Optimization Algorithm significantly enhances ANN hyperparameter optimization, resulting in a robust, efficient, and intelligent intrusion detection framework capable of improving the security and reliability of MANETs under dynamic routing attack scenarios.
Corresponding Author: Olanrewaju, S. S.	
KEYWORDS: Chaotic Tent Map, Pelican Optimization Algorithm, Artificial Neural Network, Intrusion Detection System, Mobile Ad Hoc Networks	

I. INTRODUCTION

Mobile Ad-hoc Networks (MANETs) have emerged as a crucial infrastructure-less components in wireless communications, facilitating dynamic networking among mobile devices (Shah *et al.*, 2022). The intrinsic flexibility and rapid deployment capabilities of MANETS unlike traditional network infrastructure have established MANETs as a pivotal technology for diverse applications (Hassan *et al.*, 2021; Shah *et al.*, 2022).

Mobile ad-hoc network refers to a group of wireless devices interconnected for short communication intervals (Majid *et al.*, 2022). The network is of various types such as mobile

sensor networks, mobile mesh networks, vehicle ad hoc networks and flying ad-hoc networks to mention but few. These networks are crucial for various applications such as military operations (Devika and Sudha, 2020), disaster recovery (Mohanapriya and Santhosh, 2021), large-scale public events (Rezwan and Choi, 2021), remote sensing and vehicle communications (Nazib and Moh, 2021).

Despite the usefulness of this network. Its security presents a considerable challenge owing to the dynamic and decentralised nature of nodes, many optimisation approaches and other nature-inspired Algorithms have been used for hyperparameter optimisation to improve the

classification performance of ANNs (Rahman *et al.*, 2023). Some of these approaches suffer from premature convergence, insufficient exploration of the search space and tendency to fall into local optima especially in highly dynamic MANET situations.

Therefore, the choice of Pelican Optimisation Algorithm is the fact that is a new nature-inspired optimisation algorithm that has exhibited potential exploration and exploitation abilities (Sultan *et al.*, 2023), but at same time if POA is not enhance with chaotic tent map function the algorithm may suffer from premature convergence.

This research work proposed a Chaotic Tent Map-Enhanced Pelican Optimization Algorithm to fine-tune the exploration potentiality and convergence performance of the traditional Pelican Optimization Algorithm. The proposed CTM-POA adopted in this research is to enhance the hyperparameters of an ANN for intelligent, robust and precise intrusion detection in Mobile Ad Hoc Networks

II. RELATED WORK

The intrusion detection and prevention systems (IDPS) are front-line defense security mechanisms that identify and stop malicious activity that could jeopardise network security, deviations from normal operation in data packets, communication patterns, and node behaviours (Saravanan *et al.*, 2025). Several researches have been done using advanced approaches to detect malicious activities and classify traffic patterns as either normal or attacks. These techniques encompass machine learning (ML) methods such as Least Square Regression and Least Absolute Deviation Regression (Sayan and Debika, 2022), Artificial Neural Networks and Artificial Bee Colonies (Rani *et al.*, 2020), Random Forest, KNN, and Naive Bayes (Ravi and Ramachandran, 2020). Support Vector Machine (Balli, 2021), K-Nearest Neighbours Algorithm (Farahani, 2021). Trojovsky and Dehghani (2022) employed Pelican Optimization Algorithm in one of their research works, tested on 23 benchmark functions, where POA achieved superior results in both unimodal and multimodal scenarios. Sultan *et al.* (2023) presented a deep learning Artificial Neural Network (ANN) intrusion detection system for mobile ad hoc networks. The strategy compared traditional machine learning with ANN-enhanced based models and the model achieved better detection accuracy and increase adaptability.

Consequently, numerous researchers also employed various optimization algorithms, including Particle Swarm Optimization (Shami *et al.*, 2022), Ant Lion Optimizer, Artificial Bee Colony Optimization (Rani *et al.*, 2020), Particle Swarm Optimization (Torky *et al.*, 2022), with various chaotic map function and standard intrusion detection algorithms.

Pelican Optimization Algorithm (POA)

POA is a novel meta-heuristic optimizer based on swarm intelligence, the Pelican Optimization Algorithm mimics the typical traits of pelicans while hunting (Trojovsky and Dehghani, 2022). POA employ two major strategies which are exploration phase and exploitation phase (Trojovsky and Dehghani, 2022).

At the start of each iteration, this prey is dispersed randomly over the search space, because each agent moves in the direction of the local best or global best in various algorithms, it is an unusual process. This initial stage is known as exploration. All pelicans look for a new place inside their own local search space during phase two (Trojovsky and Dehghani, 2022).

$$x_{i,j} = l_j + \text{rand} \cdot (u_j - l_j), i = 1, 2, \dots, N, j = 1, 2, \dots, m \quad (1)$$

In Equation (1), the upper and lower bounds of the j^{th} variable of the problem are u_j and l_j , correspondingly. The amount of the j^{th} parameter defined by the i^{th} solutions are $x_{i,j}$; the number of swarm members is N , rand is a random number in interval $[0, 1]$.

The pelican swarm's associates can be described by the matrix in Equation 2. Each row of this matrix represents a candidate solution, while the columns of this matrix represent the proposed values for the problem variables.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N \times m} = \begin{bmatrix} x_{1,1} & \dots & x_{1,j} & \dots & x_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \dots & x_{i,j} & \dots & x_{i,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,1} & \dots & x_{N,j} & \dots & x_{N,m} \end{bmatrix}_{N \times m} \quad (2)$$

In Equation (2), X is the matrix that represents the pelican population, and X_i represents the i^{th} individual pelican. The objective function is represented by Equation 3.

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N \times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i)_1 \\ \vdots \\ F(X_N) \end{bmatrix}_{N \times 1} \quad (3)$$

Where F is the objective function vector and F_i is the objective function value of the i^{th} candidate solution. The pelican's hunting process consists of two distinct phases, which are referred to as exploitation and exploration.

Phase I: Moving towards prey stage: At this point, pelicans are able to locate their prey and approach them. Unlike exploitation, which required flying on the water's surface, Pelicans detect and approach their prey in the first stage. The random formation of the prey's location improves POA's exploration performance. The first phase is mathematically represented by Equation (4).

$$x_{i,j}^{p1} = \begin{cases} x_{i,j} + \text{rand} \cdot (p_j - l \cdot x_{i,j}), & F_p < F_i; \\ x_{i,j} + \text{rand} \cdot (x_{i,j} - p_j), & \text{else} \end{cases} \quad (4)$$

Where F_p and $x_{i,j}^{p1}$ represent the prey objective function value, a random number l equal to one or two, and the i^{th}

pelican's new status in the j_{th} dimension based on the first phase. A new position of a pelican becomes permissible within the bounds of POA if the objective function value increases at that particular location. By employing this methodology, known as “effective updating”, and the algorithm avoids its progression through suboptimal regions. From a mathematical standpoint,

$$X_i = \begin{cases} X_i^{p1} & F_i^{p1} < F_i \\ X_i & \text{else,} \end{cases} \quad (5)$$

Where X_i^{p1} represents the updated status of the i_{th} pelican, whereas F_i^{p1} represents the value of the pelican's objective function calculated during the initial phase.

Phase II: Water spreading stage: The exploitation potential of POA is enhanced during this phase as the algorithm approaches more optimal solutions in the hunting zone. The hunting procedure is formulated as follows:

$$X_{ij}^{p2} = x_{ij} + R \cdot \left(1 - \frac{t}{T}\right) \cdot (2 \cdot rand - 1) \cdot x_{ij} \quad (6)$$

where X_{ij}^{p2} denotes the updated state of the i_{th} pelicans in the j_{th} dimension during the second phase. The constant R equals 0.2 and $R \cdot \left(1 - \frac{t}{T}\right)$ is an expression using t and T variables. The neighborhood radius of x_{ij} is determined by the iteration counter t and the maximum number of iterations T . At this point, the approval or rejection of the newest pelican position has been determined through efficient updating, as illustrated in Equation 7.

$$X_i = \begin{cases} X_i^{p2} & F_i^{p2} < F_i \\ X_i & \text{else,} \end{cases} \quad (7)$$

The new status of the X_i^{p2} is the i_{th} pelican and denotes the objective function value of the pelican. This next iteration begins once every member of the population has been updated. A series of operations guided by Equations 4 to 7 are repeated throughout this process until the execution is finished.

Optimisation with Chaotic Maps

Chaos is a recognised attribute of non-linear systems, technically characterised as unpredictability produced by a straightforward deterministic function (Elif and Bilal, 2020). Nonetheless, the unpredictable nature of chaotic randomness exhibits superior dynamical and statistical characteristics. Numerous stochastic optimisation problems sometimes become ensnared in local optima; however, research indicates that utilising chaotic map functions facilitates the escape from these issues. Chaotic tent map implements chaotic numbers as a substitute for random number sequences, which have been used and proved useful in various applications (Wang and Cheng, 2019). This methodology has been utilised in numerous research to generate varied population traits during the optimisation process, hence improving search patterns and averting early convergence.

Chaotic optimisation refers to the use of sequences produced by chaotic map functions rather than random values in an optimisation process. The initial value of the chaotic map function significantly influences its behaviour and is represented by x_0 . Numerous chaotic functions are documented in literature, including logistic, tent, sinusoidal, circular, sinusoidal, Gaussian and Singer functions (Zaimoğlu *et al.*, 2023; Ojo *et al.*, 2025). The tent map function is mathematically represented by Equation (8).

$$X_{k+1} = \begin{cases} 2x_k & x \in (0, 0.5) \\ 2(1-x_k) & x \in (0.5, 1) \end{cases} \quad (8)$$

where, x_k denotes an iterative value of the variable x at the k_{th} step, while k signifies the number of iteration steps. The hybrid chaos-based Pelican Optimisation Algorithm was created by including the chaotic tent map to optimise the exploration phase of the POA, resulting in an improved version of the algorithm. This integration is represented in Equation (9).

$$x_{ij}^{p1} = \begin{cases} x_{ij} + rand \cdot (p_j - I \cdot x_{ij}) \cdot ChaoticTentMap(x_n, r_{parameter}), & F_p < F_i \\ x_{ij} + rand \cdot (x_{ij} - p_j) \cdot ChaoticTentMap(x_n, r_{parameter}), & \text{else} \end{cases} \quad (9)$$

x_n denotes the present state and signifies the current value in the chaotic sequence. The initial value (x_0) serves as the foundation for producing the series. This value progresses across iterations to enhance diversity in the algorithm's exploration phase. $x_{(n+1)}$ represents the subsequent state derived from the current state (x_n), whereas the parameter r dictates the next place inside the chaotic sequence, directing the search process in the optimisation algorithm.

III. METHODOLOGY

This study proposes a Chaotic Tent Map-Enhanced Pelican Optimization Algorithm-Artificial Neural Network (CTM-POA-ANN) framework to improve intrusion detection in Mobile Ad Hoc Networks (MANETs). The framework integrates the classification capability of an Artificial Neural Network (ANN) with the optimization efficiency of the Pelican Optimization Algorithm (POA), while employing the Chaotic Tent Map to enhance population diversity, improve global exploration, and mitigate premature convergence during the optimization process. The objective is to determine the optimal ANN hyperparameters that maximize intrusion detection accuracy while maintaining efficient network performance under dynamic MANET environment. Figure I depicts the methodology workflow

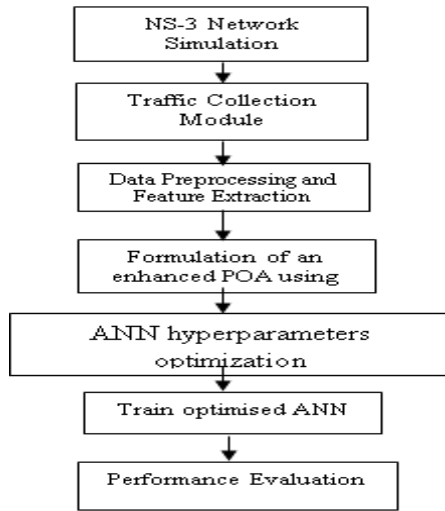


Figure 1: Diagram Showing Workflow

A. NS-3 Network Simulation

The simulation was performed in NS3 environment, featuring random waypoint mobility model, AODV routing protocol and also normal and malicious nodes were injected into the simulation process and the simulation was conducted under the same scenario in order to achieve balanced dataset.

B. Traffic Collection Module

During the simulation runs, network logs are generated consisting of both normal and attack traffics. The collected network logs are raw traces, these traces are converted to structured metrics, such as throughput, end-to-end-delay, packet loss, packet size, dropped packet, routing overhead etc.

C. Data Preprocessing and Feature Extraction

The collected simulation logs using trace outputs and FlowMmonitor outputs were saved to a particular file called NS-3 output streams. Consequently, the log files undergo preprocessing which involve handling of missing values, incomplete records removal to ensure data standardisation, enhancement, and transformation into a format suitable for effective utilisation by machine learning models. The preprocessed logs were transformed into valuable information known as quantitative descriptors (features) by the reformatting, amalgamation, and modification of the primary features into new ones that characterise the network's state.

D. Formulation of an EPOA using Chaotic Tent Map

The tent map function was used for population initialisation and reconfiguration of POA exploration in order to facilitates an equitable distribution of search agents within the search area and to increase the diversity of the initial population by replacing the conventional random initialization with the generated chaotic sequence. This process is depicted in algorithm 2

E. ANN Hyperparameters Optimization

in hyperparameters optimization of ANN each pelican represents a candidate ANN hyperparameter solution and the optimization objective maximize the ANN classification accuracy while minimizing classification error. The CTM-POA iteratively updates the pelican positions until the optimal hyperparameter combination is obtained

F. Train Optimised ANN

ANN was used as intrusion detection classifier; the classifier was supplied with optimised network features as input and the optimised network features were classifies as normal nodes or malicious nodes.

G. Performance Evaluation

The optimized CTM-POA-ANN framework was evaluated using the following classification metrics. Precision, Recall, Accuracy, F1-score.

i. **Precision** refers to ability of a classification model to correctly classify and detect all attack.

$$\text{Precision}(\%) = \frac{TN}{TN+FP} \quad (10)$$

ii. **Recall** is the ratio of accurately identified attacks to the entire number of attacks contained in the dataset.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (11)$$

iii. **Accuracy** refers to the ability of a classification model to detect all abnormality in simulation (Olagunju *et al.*, 2025).

$$\text{Accuracy}(\%) = \frac{TP+TN}{TP+FP+TN+FN} * 100 \quad (12)$$

iv. **F1 Score** refers to precision mean and recall which gives equitable model performance

$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (13)$$

H. Enhanced POA using Chaotic Tent Map

The algorithm 1 depicts the enhancement of POA using Chaotic Tent map. The Enhanced Pelican Optimisation Algorithm (EPOA) starts with the initialisation of the optimisation parameters such as the size of pelican population (N) and the maximum number of iterations (T). Each pelican represents a candidate solution corresponding to a set of ANN hyperparameters and the fitness of each solution is evaluated by the objective function of ANN.

To increase the diversity of the initial population, the Chaotic Tent Map is embedded in the initialisation stage. The Tent Map produces a chaotic sequence (r) based on the initial state and control parameter using initial x = Chaotic Tent Map (Xn, r_ parameter), resulting in uniformly distributed candidate solutions which improve the global search capability of the algorithm and decrease the possibility of premature convergence.

In each iteration the algorithm performs two optimisation phases. In the exploration phase, pelicans move towards the randomly generated prey positions to explore the search space widely with coefficient value of 0.8. The positions of

the pelicans are updated using the chaotic sequence generated by Tent Map, which improves population diversity and prevents local optima stagnation. The fitness function is cross-entropy loss on validation set

During the exploitation phase pelicans improve promising solutions and accelerate convergence to the global optimum by performing winging movements on the water surface

After each iteration, the fitness of the updated solutions is calculated and the best candidate solution is stored. This iterative process is repeated until the maximum number of iterations or the convergence criteria are satisfied.

Finally, the algorithm provides the best set of ANN hyperparameters which are then used to train the Artificial Neural Network for MANET intrusion detection. The combination of Chaotic Tent Map with Pelican Optimisation Algorithm improves the exploration, speeds up the convergence, enhances the optimisation accuracy and finally improves the classification performance of the proposed Enhanced POA-ANN model.

Algorithm I: Enhanced POA using Chaotic Tent Map

Start POA

1. Input the optimization parameters.
2. Compute pop. size (N) and the total num. of iterations (T) to be performed by the algorithm.
3. Initialization of the position of pelicans and calculate the objective Function
4. Initialize initial x and parameter r for the Chaotic Tent Map.
5. For t =1: T
6. Generate the position of the prey at random.
7. For I =1: N
8. Phase 1: Moving towards prey (exploration phase).
9. For j =1:m
10. Calculate new status of the j_{th} dimension using (3.14).
11. Use the Chaotic Tent Map to generate a chaotic sequence:
12. $X_n = \text{initial } x$
13. $\text{initial } x = \text{Chaotic Tent Map}(X_n, r_parameter)$
14. X = is the current state and r: The parameter controlling the behaviour of the map.
15. End.
16. Update the i_{th} population member using (3.15).
17. Phase 2: Winging on the water surface (exploitation phase).
18. For j=1:m
19. Calculate new status of the j_{th} dimension using (3.14)
20. End.
21. Update the i_{th} population member using (3.15).
22. End.
23. Update best candidate solution

24. End.

25. Output best candidate solution obtained by POA.
End POA.
-

The developed Chaotic Tent Map-Enhanced Pelican Optimization Algorithm-Artificial Neural Network (CTM-POA-ANN) to improved intrusion detection performance through efficient hypaperameter optimization of ANN is depicted in Figure II. The exchange of mobile nodes traffic at the network layer in order to communicate dynamically. This traffic is constantly watched for malicious activity, including Blackhole, Wormhole, and Sybil attacks. Distributed ANN agents deployed at individual nodes process the gathered network traffic, and a centralised ANN Coordinator aggregates local detection results to make precise global intrusion decisions.

The CE-POA uses a Chaotic Tent Map to improve population initialisation and parameter tuning, which boosts exploration, exploitation, convergence speed, and optimisation accuracy in order to improve the ANN's detection performance.

The IDS then receives the optimised ANN hyperparameters as optimised security information, allowing for more efficient intrusion detection with fewer false alarms. The Alert and Security Policy module creates relevant notifications and implements pre-established security policies upon detection of an intrusion. In order to lessen the impact of assaults, the Threat Response and Mitigation layer then starts countermeasures such malicious node isolation, route reconfiguration, authentication, and encryption.

Lastly, the safe Communication Layer uses safe routing techniques and ongoing network monitoring to guarantee dependable and secure data delivery. All things considered, the combination of ANN with the Chaos-Enhanced Pelican Optimisation Algorithm offers a clever, flexible, and strong security architecture that greatly increases MANETs' detection precision, effectiveness, and resistance to different network threats.

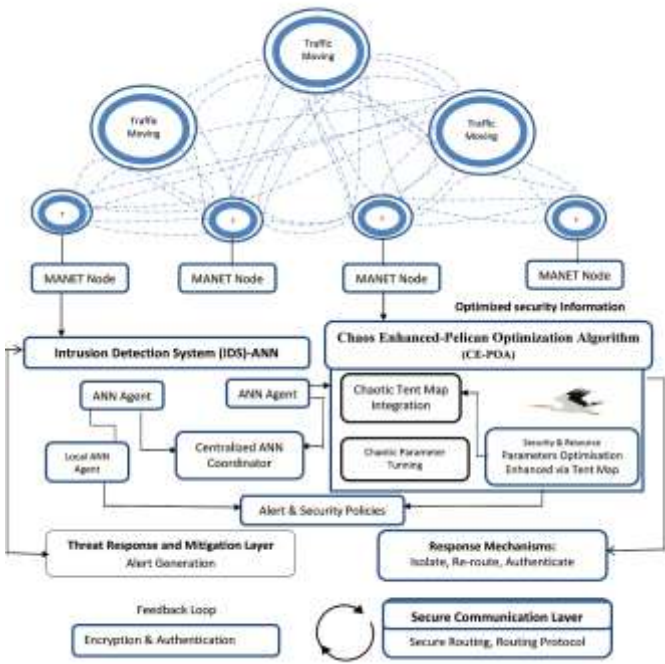


Figure II: Diagram Showing Workflow

Table 1 depicts a distinct advancement in optimisation of ANN hyperparameters, the standard ANN learning rate used is 0.001 while CTM-POA optimised ANN learning rate of 0.0036 was achieved and stability was maintained in the learning process. Neurons in layer 1 steps up from 62 to 80 in CTM-POA optimised ANN. The second layer steps up from 32 to 47 and the batch size reduced from 62 to 36 and this allows gradient precise modification. The epochs were raised from 1000 to 1500 as a result of more training in the upgraded model. The initial weight is randomly initialized until is optimised with CTM-POA. The dropout rate of 0.22 in standard ANN increase to 1.7 and this leads to robustness of the model; better convergence was achieved due to specific initialization. Therefore, the systematic enhancement of ANN hyperparameter transform a basic artificial neural network into a highly optimised system with much improved performance.

Table I: Optimised ANN Hyperparameters

Hyperparameter	ANN	CTM-POA-ANN
Learning rate	0.001	0.0036
Neuron in layer 1	62	80
Neuron in layer 2	32	47
Batch size	62	36
Epochs	1000	1500
Initial weight range	Random	Optimised ANN
Dropout rate	0.22	1.7
Fitness value	0.064	0.024

Table 2 presents the convergence performance of both standard POA and enhanced CTM-POA. The standard POA

has the initial fitness of 0.065 and best fitness value of 0.042 at iteration of 85 which indicate moderate convergence speed. The Chaotic Tent Map-Pelican Optimization Algorithm recorded the best fitness value of 0.038 with initial fitness of 0.225 at iteration of 54 this result indicates fast convergence and better optimisation of ANN hyperparameters. The results demonstrate the effectiveness of chaotic augmentation in speeding up the search thereby improving classification performance for the detection of Blackhole, Wormhole and Sybil attacks in MANETs.

Table II: Convergence Performance

Algorithm	Initial Fitness	Best Fitness	Iteration of Best Solution	Convergence Speed
POA	0.065	0.042	85	Moderate
CTM-POA	0.225	0.038	54	Faster

Table 3 provides consistent high detection ability across all three attacks using CTM-POA-ANN. The detection rate of the three attacks is as follow: blackhole (95.76%), Wormhole (94.92%) and Sybil attack (94.54%). The results indicate that the optimized ANN can effectively separate malicious activities from normal network behaviour in MANET traffic with relatively low classification error.

Table III: Attack Detection Performance of CTM-POA-ANN

Traffic Class	Precision (%)	Recall (%)	F1-Score (%)	Detection Rate (%)
Normal	96.51	95.10	94.81	97.10
Blackhole	94.13	94.86	93.92	95.76
Wormhole	94.64	96.42	96.21	94.92
Sybil	93.38	94.54	92.46	94.54
Average	94.57	95.23	94.35	95.56

Table 4 indicates that a developed CTM-POA-ANN model display a stronger classification performance compare to ANN, ANN-POA, ANN-ABC and ANN-GA models. The developed CTM-POA-ANN recorded 95.93% precision, 95.84%, recall, 95.85% accuracy and F1-score of 95.77% these results prove that the integration of Chaotic Tent Map in enhancing the exploration capacity of pelican optimization algorithm does not only optimise the ANN hyperparameters but also improve the intrusion detection capability of Artificial Neural Network.

Table IV: Classification Performance of CTM-POA-ANN Model with other Existing Models

Model	Precision (%)	Recall (%)	Accuracy (%)	F1-score (%)
ANN	85.60	85.42	85.42	85.38
ANN-POA	91.48	90.25	91.25	91.15
ANN-ABC	90.00	88.01	91.07	89.02
ANN-GA	90.01	88.11	92.01	89.11
CTM-POA-ANN	95.93	95.84	95.85	95.77

CONCLUSION AND RECOMMENDATIONS

This research concludes that the artificial neural networks intrusion-based system integrated with enhanced pelican optimisation algorithm using chaotic tent map are efficient security mechanism for mobile ad hoc networks. The developed framework yielded most significant classification performance as compared to the ANN and ANN-POA models with precision of 95.93, recall of 95.84, accuracy 95.85% and F1-score of 95.77. Hence the developed framework is suitable for intelligent intrusion detection and performance improvement in MANET environments.

Based on the results of this study, it is recommended that the proposed model should be tested using another chaotic map function such as logistic map or henon map. Furthermore, the studies should also investigate other attacks such as sinkhole. Dropping attack and delay attack

REFERENCES

- Devika B and Sudha, P. N. (2020). Power optimization in MANET using topology Management. *Engineering Science and Technology, an International Journal*, 23(3), 565–575. <https://www.sciencedirect.com/science/article/pii/S215098619302101/pdf?md5=42e35489949e754990a80084cf13edef&pid=1-s2.0-S215098619302101-main.pdf>
- Elif V. and Bilal, A. (2020) "Bird swarm algorithms with chaotic mapping," *Artificial Intelligence Review*, 53, 1373–1414, 2020
- Farahani, G. (2021). Black hole attack detection using K-nearest neighbor algorithm and reputation calculation in mobile ad hoc networks. *Security and Communication Networks*, 2021(1), 1-15. <https://onlinelibrary.wiley.com/doi/epdf/10.1155/2021/8814141>
- Hassan, M. H., Mostafa, S. A., Mahdin, H., Mustapha, A., Ramli, A. A., Hassan, M. H. and Jubair, M. A. (2021). Mobile ad-hoc network routing protocols of time-critical events for search and rescue missions. *Bulletin of Electrical Engineering and Informatics*, 10(1), 192–199. <https://mail.beei.org/index.php/EEI/article/download/2506/1885>
- Majid, M., Habib, S., Javed, A. R., Rizwan, M., Srivastava, G., Gadekallu, T. R. and Lin, J. C. W. (2022). Applications of wireless sensor networks and internet of things frameworks in the industry revolution 4.0: A systematic literature review. *Sensors*, 22(6), 1-36, <https://www.mdpi.com/1424-8220/22/6/2087/pdf>
- Nazib, A. and Moh, S. (2021). Reinforcement learning-based routing protocols for vehicular ad hoc networks: A comparative survey. *IEEE Access*, 9, 27552–27587. <https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9351930>
- Ojo, O. S., Oyediran, M. O., Olagunju, K. M., Opoola, K. B., Ogbonnia, E. O. and Adebisi, A. A. (2025). A hybrid chaotic tent map-pelican optimization algorithm for software defect prediction. *NIPES Journal of Science and Technology Research*, 7(Special Issue: Landmark University International Conference SEB4SDG 2025), 2386–2394. <https://doi.org/10.37933/nipes/7.4.2025.SI282>
- Rahman, M. T., Alauddin, M., Dey, U. K. and Sadi, S. (2023). Adaptive, secure and efficient routing protocol to enhance the performance of Mobile Ad Hoc Network (MANET). *Applied Computer Science*, 19(3), 133–159. https://yadda.icm.edu.pl/baztech/element/bwmeta1.element.baztech-0ffffd6a-7852-4fbd-9d88-53969a2882d3/c/jszabelski_9.pdf
- Rani, P., Kavita, Nhunguyen, G. and Verma, S. (2020). Mitigation of black hole and gray hole attack using swarm inspired algorithm with artificial neural network. *IEEE Access*, 8, 121755-121764. <https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9125902>
- Ravi N. and Ramachandran G. A (2020). robust intrusion detection system using machine learning techniques for MANET. *International Journal of Knowledge-Based and Intelligent Engineering Systems*, 24(3), 253-260. doi:10.3233/KES-200047
- Rezwan, S. and Choi, W. (2021). A survey on applications of reinforcement learning in flying ad-hoc networks. *Electronics*, 10(4), 1-19. <https://www.mdpi.com/2079-9292/10/4/449/pdf?version=1614067110>
- Saravanan, S., Dar, S. A., Rather, A. A., Qayoom, D. and Ali, I. (2025). Deep learning models for intrusion detection systems in MANETs: A comparative analysis. *Decision Making Advances*, 3(1), 96–110. <https://www.dmajournal.org/index.php/dema/article/view/56/51>
- Sayan, M. and Debika, N. (2022). Regression Model Estimation Using Least Absolute Deviations, Least Squares Deviations and Minimax Absolute

- Deviations Criteria. *International Journal of Research and Analytical Reviews (IJRAR)*, 9(1), 187–193.
<https://journalsweb.org/siteadmin/upload/P1215019.pdf>
14. Shah, N. El-Ocla, H. and Shah, P. (2022). Adaptive routing protocol in mobile ad-hoc networks using genetic algorithm. *IEEE Access*, 10, 132949–132964.
<https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9996161>
 15. Shami, T. M., El-Saleh, A. A., Alswaitti, M., Al-Tashi, Q., Summakieh, M. A. and Mirjalili, S. (2022). Particle swarm optimization: A comprehensive survey. *IEEE*, 10, 10031-10061.
<https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9680690>
 16. Sultan, M. T., Sayed, H. El and Khan, M. A. (2023). An intrusion detection mechanism for MANETs based on deep learning artificial neural networks. *International Journal of Computer Networks and Communications*, 15(1), 1-15
<https://aircconline.com/ijcnc/V15N1/15123cnc01.pdf>
 17. Torky, M., El-Dosuky, M., Goda, E., Snášel, V., and Hassanien, A. E. (2022). Scheduling and securing drone charging system using particle swarm optimization and blockchain technology. *Drones*, 6(9), 1–26.
<https://www.mdpi.com/2504446X/6/9/237/pdf?version=1662524781>
 18. Trojovský, P. and Dehghani, M. (2022). Pelican optimization algorithm: A novel nature-inspired algorithm for engineering applications. *Sensors*, 22(3), 1-34
<https://www.mdpi.com/1424-8220/22/3/855/pdf>
 19. Wang, L. and Cheng H. (2019). Pseudo-Random Number Generator Based on Logistic Chaotic System," *Entropy*, 21(10), 960-971.
 20. Zaimoğlu, E. A., Yurtay, N., Demirci, H., & Yurtay, Y. (2023). A binary chaotic horse herd optimization algorithm for feature selection. *Engineering Science and Technology, an International Journal*, 44.
<https://doi.org/10.1016/j.jestch.2023.101453>