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An Improved Chaotic Function Based Hapsogwo-Rl Algorithm for Intelligent Vanet Routing Optimization

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ABSTRACT
Vehicular ad hoc Networks (VANETs) work under maximal dynamic conditions where high topology changes, non-constant mobility patterns and unsteady wireless links make efficient routing a big challenge in VANETs. Standard optimization routing techniques and the presently used Hybrid PSO-GWO techniques provide performance intensification but still face problems like slow response, limited exploration, premature convergence, insufficient self-learning ability. Therefore, in order to inscribe these limitations, this paper introduces an advanced Chaotic hybrid adaptive PSO-GWO integrated with Reinforcement Learning named as (CHAPSOGWO-RL). This proposed methodology unites the exploitation strength of particle swarm optimization (PSO), the exploration strength of grey wolf optimization (GWO), where the diversity is introduced via chaotic maps, adaptive decision-making capability, and the power of reinforcement learning (RL). In this paper chaotic function are applied to HAPSOGWO-RL, where chaotic functions like logistic, tent, and gaussian maps that generates randomness that widens the search space and reduces stagnation in dynamic networks. RL is another powerful technique that fine-tunes parameters like inertia weight, convergence rate, routing overhead, and acceleration coefficient. The proposed technique is compared with traditional protocols and swarm-based protocols like the ROANCO algorithm, genetic algorithms and K-means clustering algorithms. Then the results show that the proposed method is better in optimization, like improved delivery ratio, high throughput, minimum overhead, delay, and packet loss. CHAPSOGWO-RL is an intelligent routing engine capable of predicting connectivity, breakage, stable forwarders etc. This algorithm is implemented in NS2.35 with SUMO based vehicular traces. Simulation results show that the proposed methodology improves the throughput, increases the delivery ratio, lowers delay, and lowers the packet loss. Overall, proposed algorithm represents a highly adaptive and self-evolving routing framework designed for VANET applications, chaos theory reinforcement learning, and the strengths of swarm intelligence.

Keywords: VANET, Routing, Particle Swarm Optimization, Grey Wolf Optimization; Reinforcement Learning, Chaos Theory, Hybrid Algorithm, Adaptive Optimization.

1. Introduction

Vehicular Ad-hoc Networks (VANETs) form an indispensable foundation of modern Intelligent Transport Systems (ITS) that provide efficient communication between vehicles and roadside infrastructure. VANETs are used in a variety of applications such as cooperative driving, real-time traffic control, accident prevention and hazard warnings, and intelligent mobile services. VANETs provides efficient routing strategies that can be stable in rapidly changing topology, diverse vehicle speed, and fluctuating node distributions. Like traditional networks, VANETs provides dynamic and unpredictable routing techniques, where rapid disconnections and high mobility continuously affect routing performance [1][2]. The traditional routing protocols like AODV, DSR, and GPRS are suffer from various conditions where maintaining efficiency in the network is extremely difficult. Therefore, increased delays, packet loss, and unstable links and paths between nodes. One of the most important advantages of using VANET is their ability to increase road safety [3]. VANETs enables real time communication and allowing fastly exchange of safety information in such conditions like: warning alerts, collision warmings, lane change notification and critical road conditions. This proactive information reduces accidents, minimize injury sternness and contributes to safe and more reliable transportation system [4].
Another side the Swarm intelligence (SI) techniques has represented as a promising solution to limitations of traditional routing protocols because of their ability to cope with complex, nonlinear, and time-varying optimization problems. Swarm-based intelligence algorithms are inspired by the collective behavior of natural organisms, where simple agents collaborate to find the optimal solutions [5]. In VANET routing, swarm algorithms provide adaptive, decentralized, and robust route optimization under highly dynamic conditions.

Some swarm Algorithms such as Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) simulate natural behaviours where PSO defines collaborated movement in bird flocks, while GWO defines hierarchical hunting mechanisms of grey wolves like alpha, beta and gamma [6]. These methods provide much better adaptability and accuracy in routing decisions as compared to traditional protocols. However, each algorithm suffers from some weaknesses, PSO may lose diversity and converge prematurely, while GWO can be sensitive to initial population settings and may converge slowly. Although hybrid PSO–GWO methodology attempt to combine the strengths of both algorithms for better routing but this hybrid method is still lack dynamic adaptivity and are not able to adjust routing effectively in highly dynamic VANET environments [7]. By integrating swarm intelligence with adaptive control, chaotic mapping, or reinforcement learning, routing frameworks can achieve faster convergence, enhanced exploration–exploitation balance, and robust decision-making. Consequently, swarm-based intelligence has emerged as a powerful and effective paradigm for designing intelligent, scalable, and resilient VANET routing solutions [8][9].

Reinforcement Learning (RL) is a branch of machine learning in which an autonomous agent learns optimal decision-making strategies through continuous interaction with a dynamic environment. Unlike supervised learning, RL does not rely on labelled datasets; instead, the agent observes the current state of the environment, performs an action, and receives feedback in the form of rewards or penalties. Over time, the agent learns a policy that maximizes cumulative reward, enabling it to adapt its behavior according to changing environmental conditions. As a result, VANET protocols may suffer from increased routing overhead, higher packet loss, and unstable route selection under high mobility scenarios.

Reinforcement Learning offers a promising solution to these challenges by enabling intelligent, adaptive, and self-learning routing decisions in VANETs. In an RL-based routing framework, each vehicle or routing agent can dynamically evaluate network conditions such as link stability, node velocity, traffic density, delay, and packet delivery ratio. Based on these observations, the agent selects routing actions—such as next-hop selection or route maintenance strategies—and continuously improves its decisions using feedback obtained from network performance metrices [10][11].

One of the key advantages of RL in VANET routing is its ability to learn optimal routing policies without requiring a complete global view of the network. This decentralized learning capability is particularly suitable for VANETs, where maintaining up-to-date global topology information is impractical. Moreover, RL enables real-time adaptation to environmental changes, allowing routing decisions to evolve as vehicular mobility patterns and traffic conditions change [12][13]. When integrated with metaheuristic optimization techniques such as Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO), Reinforcement Learning further enhances routing performance. While PSO and GWO efficiently explore and exploit the solution space to identify high-quality routes, RL acts as a supervisory intelligence that dynamically adjusts algorithm parameters, balances exploration and exploitation, and selects the most appropriate routing strategy based on current network states [14]. This hybrid learning-optimization approach leads to improved convergence speed, enhanced route stability, reduced end-to-end delay, and higher packet delivery ratios [15].

Previous research has explored adaptive tuning and increased parameter control, but some approaches depend on fixed or manually adjusted parameters that do not respond to changing vehicular conditions such as changing density of network, high-speed fluctuations, or unpredictable mobility. Another significant research gap is based on the absence of self-learning capabilities within presenting hybrid metaheuristics, which limits their ability to adapt themselves autonomously. Moreover, random mobility patterns in urban traffic can confuse traditional optimizers and lead to early stagnation or imbalance between exploration and exploitation. VANET routing involves selecting stable, high-quality links under dynamic mobility. Optimization techniques such as Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Reinforcement Learning (RL), and chaotic maps improve search capability, adaptability, and convergence. The integration of these methods enhances reliability, throughput, delay, and packet delivery ratio in vehicular environments.

To bridle these challenges, this study presents CHAPSOGWO-RL, a Chaotic Hybrid Adaptive PSO–GWO combined with Reinforcement Learning. This framework unites three powerful computational paradigms that are explained below:

1. Chaotic Function: It represents logistic, tent, and Gauss maps used for the search space and initiates-controlled randomness to prevent idleness [17][18].
2. Hybrid Swarm Intelligence: The global convergence behavior of PSO is fused with the hunting mechanisms of GWO to achieve a realistic search process [19].
3. Reinforcement Learning: An RL agent monitors real-time performance metrics from time to time and dynamically adjusts parameters such as inertia weight, acceleration coefficients, chaos strength, and grey wolf hierarchy factors[20].

By combining these components, CHAPSOGWO-RL introduces a fully adaptive and optimized routing engine, that is capable of predicting route errors and failures, choosing next nodes, and different mobility scenarios. Therefore, this methodology is developed using NS2 using SUMO-generated mobility traces and compared with traditional protocols and swarm-based protocols like the ROANCO algorithm, genetic algorithms and K-means clustering algorithms. Then the results show that the proposed method is better in optimization, like improved delivery ratio, high throughput, minimum overhead, delay, and packet loss. Overall, the proposed algorithm presents a major advancement in the VANET routing framework. By combining chaotic function, hybrid method, and reinforcement learning makes this work becomes more intellectual, unique and better [21]. This work defines a strong foundation for highly efficient, robust and self-evolving routing strategies required for future intelligent transportation and autonomous vehicular systems.

2. Literature Review

Vehicular Ad Hoc Networks (VANETs) present high mobility, frequent disconnections, and dynamic topology changes, requiring intelligent routing solutions. The literature review examines traditional, swarm intelligence, chaos-based, reinforcement learning, and hybrid algorithms to identify research gaps that motivate the proposed CHAPSOGWO-RL approach.

Ayansiji et al. (2025) presents a novel improvement to the Grey Wolf Optimizer (GWO) by combining two important methods, such as adaptive parameter control through nonlinear decay and chaotic population initialization using the logistic map, to create a novel upgraded Grey Wolf Optimizer (EGWO). The premature convergence and inadequate exploitation in high-dimensional search spaces are the common drawbacks in traditional GWO. The adaptive strategy ensures a dynamic balance between exploration and exploitation, while the chaotic initiation encourages early-stage variation. EGWO is in 30 dimensions, such as Compared to standard GWO, it achieves up to a 30% faster convergence and increases 25% in solution accuracy. Statistical tests confirm EGWO is a competitive algorithm for solving complex and large optimization problems [22].

Yanhua Lei et al. proposes an enhanced Gray wolf optimization (GWO) algorithm. First, a novel individual memory optimization strategy is generated to expand the population's exploration scope and lower the risk of individuals pursuing misguided search trajectories. Second, a position update strategy using differential variations to balance the local and global search mechanism of individual populations. Lastly, a discrete crossover strategy is proposed to enhance the information diversity between individuals. By combining these three enhancement strategies with the GWO, a novel enhanced gray wolf optimization (IGWO) algorithm is created, which is used to analyse global and local search capabilities and also demonstrates accelerated convergence performance. In comparative analyses empirical findings suggest that the IGWO algorithm effectively resolves the optimization problem, demonstrating performance linked to other benchmark algorithms [23].

Halimjon Khujamatov et al. (2024) proposed work defines an energy-efficient clustering technique using a chaotic genetic algorithm, and creates an energy-saving routing technique using a bio-inspired grey wolf optimizer algorithm. The proposed chaotic genetic algorithm–grey wolf optimization (CGA-GWO) is designed to cut overall energy dissipation by choosing energy-aware cluster heads and designing an optimal routing path to reach the destination. The simulation results represent the improved functionality of the proposed system when integrated with three more relevant systems, using metrics such as the number of live nodes, average remaining energy level, packet delivery ratio, and overhead attaching with cluster formation and routing mechanism [24].

Zhiyong Luo et al. (2022) CO-GWO method to ensure that the local optimization can be reached in time and a much better optimal value can be received. The population of the algorithm is divided between two parts: one is the better part of each iteration, and the other is created by the tent map and OBL. The value of each iteration used to search for a better value of the next generation accelerates the search speed and increases optimization ability. Therefore, in order to balance the relationship between exploration and exploitation, the polynomial decay function on the 2-decay method is used to control the parameter. So,23 benchmark functions are tested, and CO-GWO is compared with five heuristic optimization algorithms. Experimental results show that the performance and stability of CO-GWO are better than other optimization algorithms [25].

Mahmoud Khatab et al. (2024) provide a deep explanation of the gray wolf optimization technique to solve difficult problems related to optimization. In this paper, we introduce a novel mechanism for updating agents' positions, which aims to improve the algorithm's effectiveness and efficiency. To validate the working of our proposed method, comprehensive experiments are carried out and compare the results with the original Grey Wolf Optimization technique. The comparative analysis demonstrates that the proposed method achieves

greater optimization outcomes. These outcomes underscore the potential of our method in addressing optimization challenges effectively and efficiently [26].
Rodrigo Olivares et al. (2023) present an adaptive method to control parameters during reinforcement learning for the PSO (particle swarm optimization). The main aim of this paper is to adjust parameters to achieve better learning quality and adapt to problems dynamically. This proposal integrates Q-L learning for parameter switches for optimizing algorithms. The applied technique includes a shared Q table, tables for parameters, and flexible state representation form one state to another. It uses the knapsack problem for the NP- hard class. So, it can be explained by a mathematical combinatorial problem that involves a set of items with multiple attributes to maximize the total values. Experimental results are carried out to compare the results achieved through hybridization, which can improve the quality of the solutions [27].
Jan Lansky et al. (2022) proposed a number of RL-based routing methods. Firstly, we have marked an introduction to RL, the Markov decision framework, and their characteristics, and then we have categorized and deeply introduced RL-based routing approaches with esteem to the learning framework, learning model, learning algorithm, learning process, and the routing algorithm. In this paper, we strained to help researchers find a new view of reinforcement learning applications to design routing structures. This supports researchers to appropriately and accurately understand how these routing methods are considered in VANETs and distinguish existing challenges to attempt to remove them. In the future, we will study reflective reinforcement learning and review its effect on the routing methods in VANETs. These new tactics have been applied in numerous areas and presented auspicious results in VANETs to improve their performance and efficiency [28].
Ibrahim Berkan Aydeilek et al. (2021) proposed the HFPSO algorithm that was replaced with chaotic values that were generated by maps. The HFPSO algorithm is a metaheuristic algorithm where the positive effect of chaotic mapping on the proposed algorithm was demonstrated. The proposed algorithm evaluates how it reacts to chaotic functions. Then the performance of the CHFPSO algorithm on 10 different chaotic maps is examined. Then it is stated that the chaotic maps represented successful results for HFPSO algorithm. Extensive experiments on CEC 2015 benchmark snags and in the task of five different constraint problems validate the robustness of CHFPSO algorithms. In the future, we will make a profound investigation of the tradition of CHFPSO on discrete optimization problems [29].

3. Methodological Framework Of The Proposed Chapsogwo-Rl Algorithm

This proposed methodology presents the CHAPSOGWO-RL algorithm, a Chaotic based Hybrid Adaptive Particle Swarm Optimization and Grey Wolf Optimization integrated with Reinforcement Learning. This algorithm is used to achieve intelligent and extremely stable routing decisions in Vehicular Ad-hoc Networks (VANETs). The inclusive methodology is designed to stunned the confines of traditional routing protocols and existing swarm intelligence-based algorithms by incorporating chaotic function assortment, hybrid exploration and exploitation mechanisms, and RL-based self-learning parameter adaptation [30].

3.1. Functional Model of the Proposed Framework

The goal of the suggested cluster head section and clustering method for VANETs is to enhance the network communication and coordination effectiveness. Vehicles and roadside units, which are all outfitted to provide both V-V and V-I communication, make up the network in this framework. A dynamic clustering approach is used, in which groups are formed according to the variables, including communication range and inter-vehicle distance. A chosen cluster head (CH) is in charge of overseeing communication inside each cluster. Criteria like overall reliability, link stability, and vehicle velocity are used to select the CH. The CH's condition is continuously monitored, and if it becomes unstable and unavailable, a seamless handover mechanism chooses a replacement CH without interfering with communication. Before sending data to next network layer, CHs aggregate it to remove unnecessary information, increasing bandwidth usage and lowering overhead.

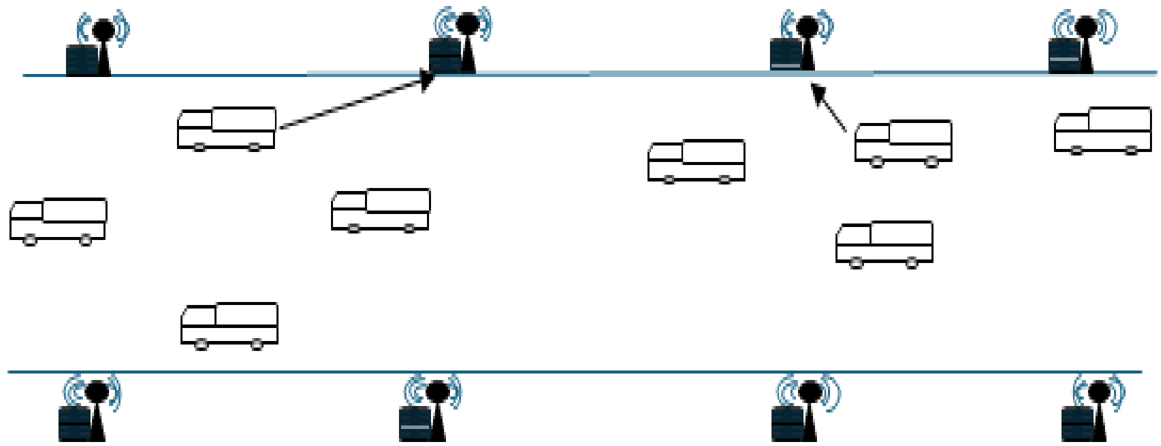

Figure 1: Deploy of Network

As figure 1 indicates, the positioned VANET has a finite number of vehicle nodes and purposefully positioned RSUs. This network facilitates unified V2V communications that are enabling vehicles to communicate with each other directly. In Additionally, the system supports Vehicle-to-Roadside Unit (V2I) communication, leveraging RSUs for infrastructure-related communication.

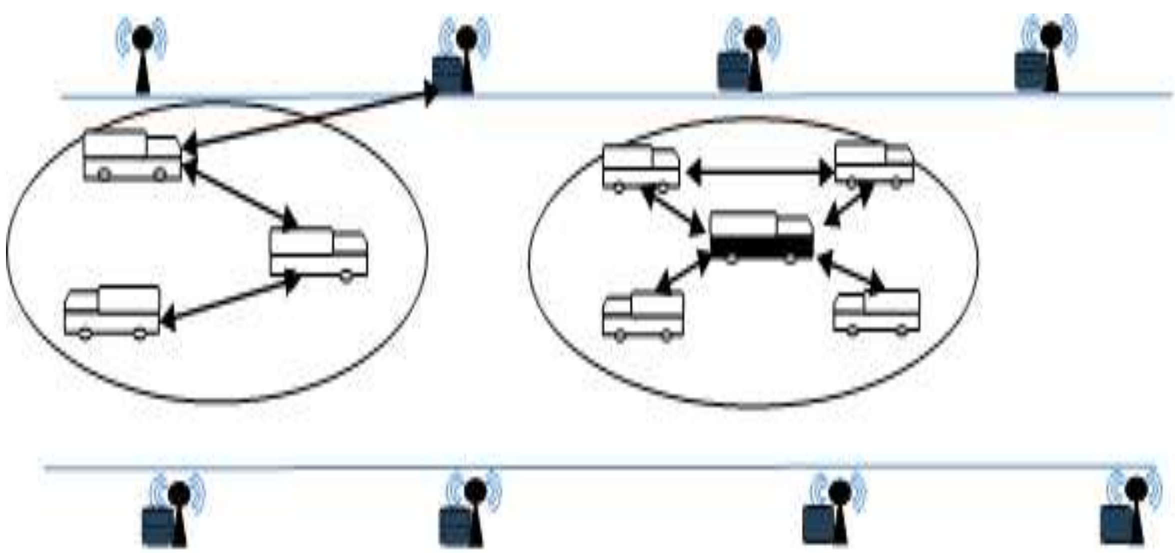

Figure 2: Process of Selecting Cluster Head

As shown in figure 2, communication efficiency is maximized by dividing the VANET network into clusters according to vehicle location. One of the most important tasks is choosing a cluster head. Effective connectivity is ensured by the selected vehicle's largest direct communication range within the cluster. One important factor of VANET is to ensures continuous communication is stability. A hybrid optimization algorithm approach that combines PSO & GWO is used in the cluster-head selection procedure. While GA refines the solution by taking into account variables like vehicle speed, battery status, and network load, PSO starts investigating possible options based on range and stability. By taking into account both immediate communication and long-term network effectiveness, this method guarantees the selection of the best cluster head. The end product is a dynamic VANET clustering system that effectively identifies cluster heads using a CHAPSOGWO-RL algorithm for promoting reliable, robust, and adaptable network performance.

3.2 Existing HAPSOGWO-RL

The HAPSOGWO-RL (hybrid adaptive PSO_GWO using Reinforcement Learning) is an advanced optimization framework designed to avoid the limitations of traditional PSO, GWO and conventional VANET routing protocols. It merges the assets of all these techniques and eliminates their weaknesses through Chaotic function adaptability. The explanation of all these techniques is given below:

1. Hybrid PSO-GWO

The traditional PSO (Particle swarm optimization) has fast convergence speeds, but it easily gets trapped in local ideal solutions. It has also faced difficulty in distant search regions as well. On the other hand, the GWO (grey wolf optimization) explores well but has slower convergence and exploitation. So, to overcome these issues related to PSO and GWO, to hybridization of these algorithms provides better global search, fast convergence and also has reduced local trapping [31]. By doing this, the GWO handles global exploration (finding areas for good results) and PSO handles exploitation (finding the best results very quickly).

2. Adaptive Mechanism

Another technique included in the hybrid PSO-GWO is the Adaptative mechanism. Adaptive means parameters are changed automatically. These parameters are depended on the network conditions. In standard PSO & GWO inertia weight (ω), acceleration coefficient (c1, c2), and "a" value in GWO remain fixed if VANET having poor performance [32]. In this adaptive model, parameters are changed dynamically using reinforcement learning (RL) and chaotic function maps generate nonlinear variability while included in adaptive methods. This gives high exploration and exploitation in highly mobile networks. Then the route becomes stable and gives the better response to immediate changing topology. The following Example shows this method:

$$\omega t = \omega \min + Zt\,(\omega \max - \omega \min)\,\omega \max) \ldots\ldots (1)$$

3. Reinforcement Learning (RL)

Reinforcement Learning is the intelligent decision-making technique in this hybrid model. It inspects the network and reads the node mobility link stability, packet delivery ratio, delay, queue length, connectivity patterns. The RL selects the best parameters of PSO, like (ω, c1, c2), and the optimal GWO parameters like (a, A, C), when to change between PSO and GWO phases. So, in which chaotic function map is to be use to update adaptive intensity. The RL agent receives recompense based on routing performance. If performance improves, the it increases rewards. If performance declines, then it adjusts RL parameters. So, it makes the system more intelligent, self-learning and self-adaptive [33]. The RL function is displayed in the following example:

$$R = \alpha \cdot PDR - \beta \cdot Delay - \gamma \cdot Overhead \ldots . (2)$$

4. Algorithmic Framework of the Proposed CHAPSOGWO-RL Method

The proposed CHAPSOGWO-RL framework integrates chaotic dynamics with hybrid swarm intelligence and reinforcement learning to optimize routing decisions in highly dynamic VANET environments. Initially, the network topology is established by deploying vehicles and RSUs with V2V and V2I communication capabilities. A chaotic map is initialized to generate deterministic yet non-repetitive control values, which are utilized throughout the optimization process.

In the first stage, a Chaotic Adaptive Particle Swarm Optimization (CA-PSO) module is employed, where inertia weight and acceleration coefficients are dynamically adjusted using chaotic sequences. This enhances swarm diversity and prevents premature convergence during route exploration. Parallelly, a Chaotic Grey Wolf Optimization (CGWO) mechanism updates the leader wolves (α, β, δ) using chaos-controlled parameters to balance global exploration and local exploitation. The best solutions obtained from both PSO and GWO are fused to form a hybrid candidate routing decision. Reinforcement Learning is then applied to adaptively select optimal actions such as next-hop selection or cluster head assignment. Chaos-driven ε-greedy exploration ensures effective learning while avoiding repetitive routing behavior[34].

Finally, the RL agent updates its policy based on a reward function derived from network performance metrics including Packet Delivery Ratio, end-to-end delay, and packet loss. The iterative interaction between chaotic optimization and learning enables the proposed framework to achieve superior routing stability, adaptability, and performance in VANET scenarios.

The superior performance of CHAPSOGWO-RL can be attributed to three main factors:

1. Chaotic Control: Ensures non-repetitive, adaptive parameter tuning
2. Hybrid Optimization: Combines fast convergence (PSO) with strong exploitation (GWO)
3. Reinforcement Learning: Enables intelligent, experience-based routing decisions

The synergy of chaos, swarm intelligence, and learning makes the proposed algorithm highly suitable for dynamic VANET environments, where traditional routing protocols fail to adapt efficiently. The Results confirm that integrating chaos with hybrid PSO–GWO and reinforcement learning significantly enhances packet delivery, reduces delay, and improves throughput in highly dynamic VANET scenarios [35].

4.1 Chaotic Function

The nonlinear deterministic mathematical functions known as chaotic function maps produced extremely highly predictable sequences. Because of their high sensitivity to initial conditions, the generated values appear random even though their evolution is guided by accurate equations. In order to improve population variety, bolster exploration, and avoid premature convergence, chaotic maps are frequently employed in metaheuristic optimization methods [36].

By generating a variety of search patterns, chaos in optimization aids the algorithm in escaping local minima. Controlled randomness from chaotic sequences can dynamically alter important parameters like the convergence coefficient in GWO or the inertia weight in PSO. This enhances the hybrid and adaptive system's capacity for global search [39][40]. The Chaotic maps are incorporated into the suggested hybrid adaptable PSO_GWO employing Reinforcement learning to provide adaptable coefficients and exploration parameters. By choosing when and how to employ chaotic perturbations, RL enables the optimizer to dynamically balance exploration and exploitation [37]. The chaotic function is defined by the below diagram:

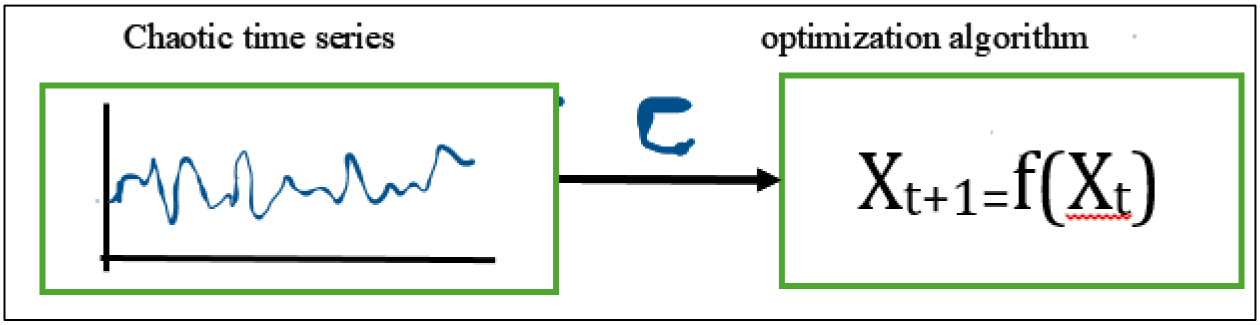

Figure.3 Chaotic function

There are three types of chaotic functions maps like Logistic map, Tent map and Gaussian map. These function maps are collaborated into adaptive hybris PSO-GWO to improve randomness, convergence and prevent stagnation dynamically to integrate with parameters by using chaotic functions [38].

Table:1 Different maps of Chaotic functions

Logistic Map	Tent Map	Gauss (Gaussian) Map
$x_{t+1} = \mu x_t(1 - x_t), \mu \in [3.57,4]$ Recommended: $\mu = 4$ ….. (3) x_t = current chaotic value x_{t+1} = next chaotic value μ = control parameters (e.g. simple and strong randomness and used in PSO, GWO GA, DE algorithms).	$x_{t+1} = \begin{cases} \frac{x_t}{a}, & x_t < a \\ \frac{1 - x_t}{1 - a}, & x_t \geq a \end{cases}$ Usually: $a = 0.5$ …… (4) x_t = current chaotic value x_{t+1} = next chaotic value (e.g. produce uniform randomness and increase convergence stability).	$x_{t+1} = \begin{cases} 0, & x_t = 0 \\ \frac{1}{x_t} \bmod 1, & x_t \neq 0 \end{cases}$ …… (5) x_t = current chaotic value x_{t+1} = next chaotic value (e.g. has strong chaotic properties and much better for exploitation and exploration).

Adding Chaos to PSO &GWO Equations

Replace random numbers r_1and r_2with chaos map output C_t:

$v_i(t+1) = wv_i(t) + c_1 C_t \left(p_i - x_i(t)\right) + c_2 C_{t+1} \left(g - x_i(t)\right)$.....(6)

Adaptive chaotic inertia weight: $w = w_{min} + (w_{max} - w_{min}) \times C_t$....(7)

Position update in PSO $x_i(t+1) = x_i(t) + v_i(t+1)$ .... (8)

$$A_1 = 2a \cdot C_t - a$$
$$C_1 = 2C_{t+1} \;\ldots.\; (9)$$

Similarly, for β and δ wolves. Final GWO update with chaos:

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \;\ldots\; (10)$$

Where C_tand C_(t+1)come from Logistic / Tent / Gauss map. Where, C=C_t "(chaos-based adaptive weight)."

Chaotic Hybrid adaptive PSO–GWO using RL

$X_{hybrid} = C_t X_{PSO} + (1 - C_t) X_{GWO}$...(11)

In Eq. (6) the PSO velocity is replaces classical random scalars r_1,r_2with chaotic scalars C_tand C_(t+1). Eq. (7) defines the Inertia weight w(t)is driven by chaos, when C_tis high you get higher inertia (more exploration), when low you get lower inertia (more exploitation). Eq. (8) defines the Standard position update after velocity is computed. Eq. (9-10) defines the GWO coefficient Aand Care computed using chaotic scalars; each leader α,β,δcan use independently-seeded chaotic streams C_t^((α)),C_t^((β)),C_t^((δ))if needed. The absolute-difference update is standard GWO but with chaos. Eq. (11) defines the Final hybrid solution is a convex mix between the PSO updated candidate and the GWO updated candidate weighted by the same chaotic scalar C_t. This lets chaos control the relative influence of PSO vs GWO dynamically. So, the RL agent observes network performance and adjusts inertia weight (w), cognitive and social coefficients (c1, c2), convergence factor (a), and hybridization factor (C). Chaotic maps generate dynamic values to perturb search boundaries.

The block diagram of proposed method is given below in Figure 4. In block diagram the working of existing algorithm is shown where chaotic function is applied to hybrid adaptive PSO and GWO to increase the randomization, where nodes are designated randomly and the reinforcement update the co-efficient and exploration of particles.

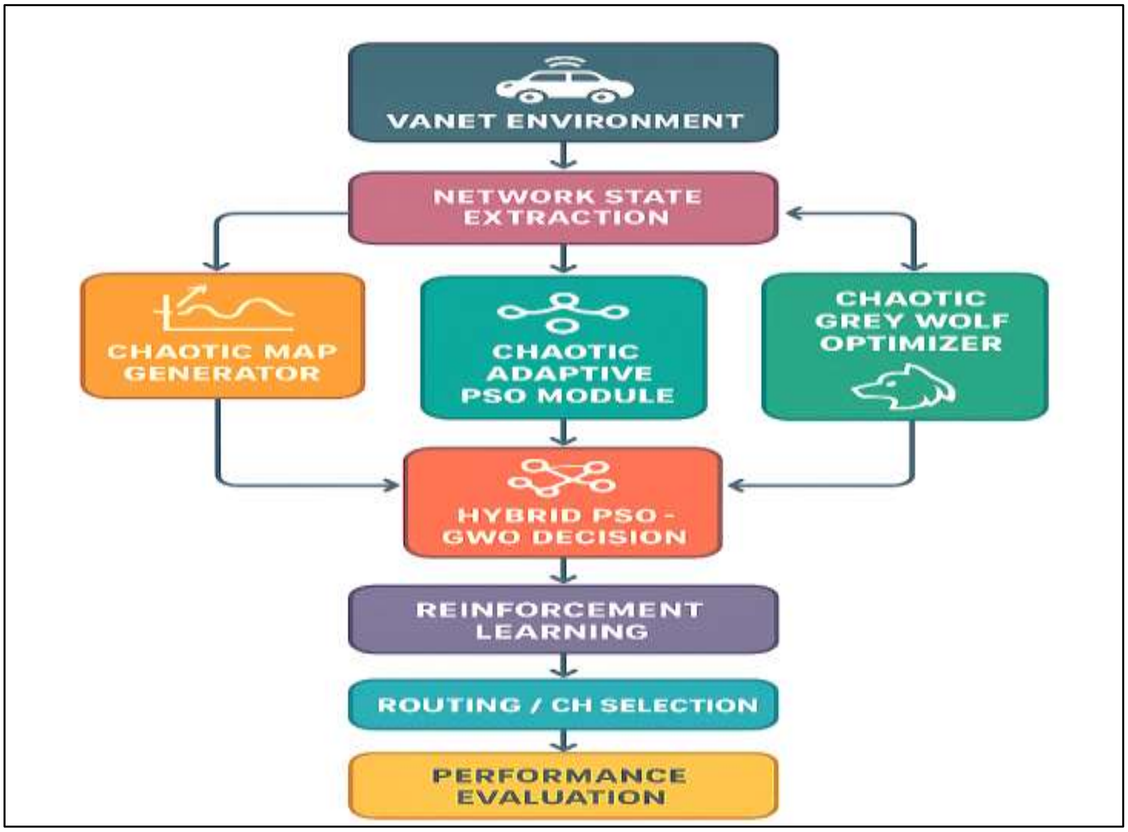

Figure 4: Block diagram of proposed algorithm

While integrating chaos into both PSO and GWO by replacing their random coefficients with chaotic scalars C is generated from Logistic, Tent, Gauss maps or a tuneable mixture. The chaotic scalar tempers inertia weight, cognitive or social coefficients, and the convex mixture weight between PSO and GWO. Reinforcement learning observes normalized network metrics (PDR, Delay, Throughput, Packet Loss) and adapts chaotic intensity and hybridization parameters online to maximize a weighted reward, permitting dynamic shifting between exploration and exploitation in swiftly changing VANET topologies. Below Figure 5 shows the working flow of proposed algorithm in flow diagram:

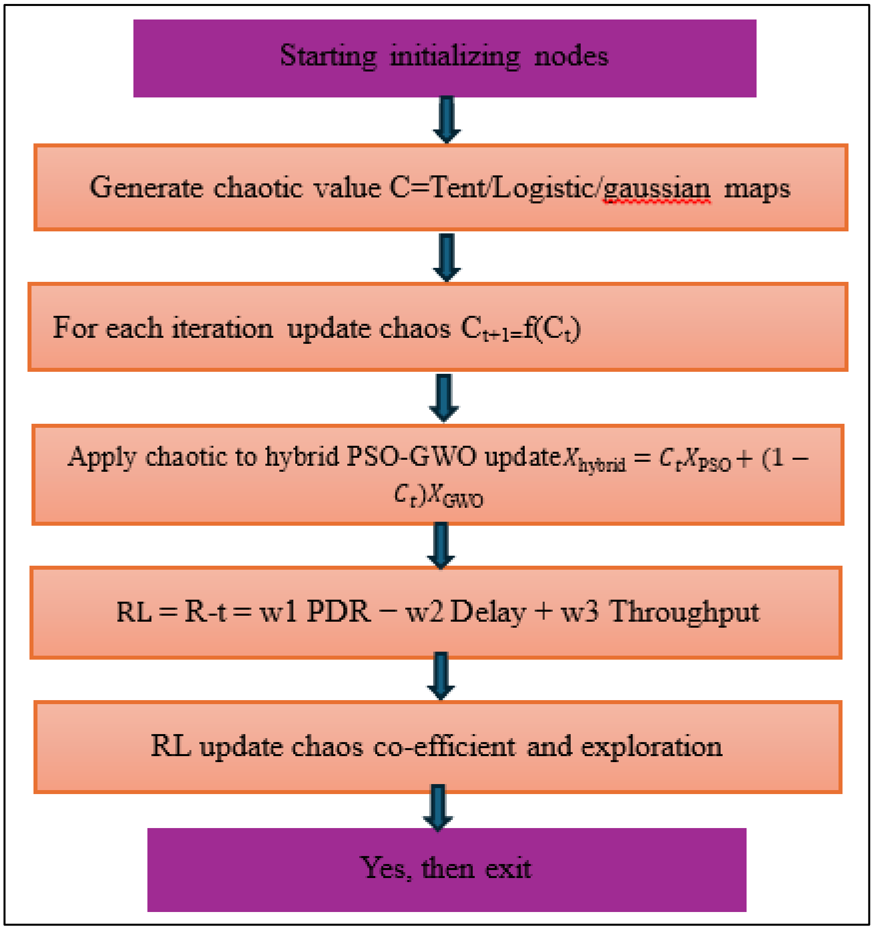

Figure 5: Flow diagram of CHAPSOGWO -RL

5. CHAPSOGWO -RL algorithm

Abbreviations
VANET – Vehicular Ad-hoc Network
GWO – Grey Wolf Optimizer
PSO – Particle Swarm Optimization
CH – Cluster Head
α, β, δ – Top three ranked cwolves in the hierarchy (alpha, beta, delta)
P – Personal Best Position
G – Global Best Position
X – Position Vector
V – Velocity Vector
t – Current Iteration
t_max – Maximum Iterations
r1, r2 – Random Numbers in [0,1]
A, C – Coefficient Vectors
w – Inertia Weight
c1, c2 – Acceleration Coefficients
Ct,Ct+1 – Chaotic function
Pseudocode
Input: Max iterations (t_max), number of wolves/particles (N), position bounds
Output: Optimal cluster head positions
1. Initialize population (wolves/particles) Xi (i = 1 to N) randomly
2. Initialize velocities Vi for PSO components
3. Evaluate fitness of each Xi
4. Identify α (best), β (second best), δ (third best) wolves

5. Initialize personal best Pi and global best G
6. Generate chaotic value C=Tent/Logistic/gaussian maps
For each iteration update chaos Ct+1=f(Ct)
8. For t = 1 to t_max do:
a = 2 - 2 * t / t_max // Convergence factor for GWO
For each particle i = 1 to N do:
// ------- GWO Part: Grey Wolf Position Update --------
For each dimension d do:
Compute A = 2 * a * rand() - a
Compute C = 2 * rand()
Compute Dα = |C * Xα[d] - Xi[d]|
Compute Dβ = |C * Xβ[d] - Xi[d]|
Compute Dδ = |C * Xδ[d] - Xi[d]|
Compute X1 = Xα[d] - A * Dα
Compute X2 = Xβ[d] - A * Dβ
Compute X3 = Xδ[d] - A * Dδ
GWO_X[d] = (X1 + X2 + X3) / 3
// ------- PSO Part: Particle Swarm Update -----------
For each dimension d do:
Vi[d] = w * Vi[d]
+ c1 * rand() * (Pi[d] - Xi[d])
+ c2 * rand() * (G[d] - Xi[d])
PSO_X[d] = Xi[d] + Vi[d]
// ------- Combine GWO and PSO ----------------------
For each dimension d do:
Xi[d] = (GWO_X[d] + PSO_X[d]) / 2
Evaluate new fitness of Xi
Update personal best Pi if fitness improved
Update α, β, δ if better solutions found
Update global best G from Pi values
7. Add chaotic function X_"hybrid" =C_t X_"PSO" +(1-C_t)X_"GWO"
update velocities using chaotic r_1,r_2, update positions and compute A,Cusing chaotic values and update positions based on alpha/beta/delta.
8.Compute RL reward, change in fitness or VANET metrics
9. End For
10. Return best solution G (optimal cluster head positions)

6. MULTI-METRIC COMPARATIVE EVALUATION OF THE PROPOSED ALGORITHM

In this research the three methods are compared with the proposed technique, that are ROANCO (remora optimization), K-means clustering and Genetic algorithms. These algorithms are likewise a powerful technique and produces the optimal outcomes while applying in VANET. But the proposed approach employs chaotic adaptive method that applies on hybrid PSO and GWO using reinforcement learning, that makes this algorithm more unique and optimal and gives superior results. Below is a comparison of these algorithms:

1. ROANCO (remora optimization) routing algorithm

ROANCO combines reinforcement learning paired with network optimization algorithm to choose dependable routes. Based on dynamic patterns of link quality, it modifies its routing behaviour. However, the training burden increases when node mobility is exceedingly high.

2. K-Means Clustering-Based Routing

This protocol builds clusters using Euclidean distance or mobility features. Cluster heads control routing inside clusters while lowering routing overhead. But it struggles when vehicular movement excessively irregular or erratic.

3. Genetic Algorithm (GA) Based Routing

Genetic algorithm explores routing patterns utilizing evolutionary operators including selection, crossover mutation and termination etc. It is an AI based algorithm and most popular algorithm known for good results. It enhances path dependability but suffers from sluggish convergence and high computational cost in rapidly changing VANET's

4. CHAPSOGWO-RL – Proposed algorithm

For quicker convergence that avoids local traps, the suggested method combines features of PSO & GWO, for exploitation and exploration, Reinforcement learning for optimal decisions, and chaotic function for randomness. This enhances stability, QoS, and throughput by making routing extremely adaptive in extremely dynamic VANET situations. The table displays a through comparison of various algorithm:

Table.2 Comparison of proposed algorithm with other algorithms

Features	ROANCO	K-means clustering	Genetic algorithm	CHAPSOGWO-RL(proposed)
Routing Type	Learning- based	Cluster- based	Meta-heuristic optimized	Hybrid PSO-GWO +RL + Chaos
Mobility adaptation	High	Medium	Medium	Very high
Cluster Stability	Moderate	High clustering	Low dynamic GA	Very high
Computational	High	Medium	High	Optimized using adaptive chaos
Scalability	Good	Excellent	Good	Excellent
Convergence speed	Medium	Fast	Slow-Medium	Faster chaotic PSO-GWO
Packet delivery Ratio	High	Medium	Medium-High	Highest
End-to-End delay	Low	Medium	High	Lowest
Throughput	Low	Medium	High	Lowest
Packet loss	Low	Medium	High	Very low
Best Environment	Urban high mobility	Highway & uniform layout	Sparse to medium density	Any dynamic scenario (VANET)

7. Results And Discussion

In this research, the performance of proposed algorithm CHAPSOGWO-RL (Chaos-Driven Hybrid Adaptive PSO-GWO with Reinforcement Learning) routing scheme is accessed against existing optimization based VANET algorithms such as ROANCO, K-means clustering, and Genetic Algorithm. The metrics considered it Overhead analysis, End-to-End Delay, Throughput, and Packet loss ratio, with the number of nodes form 50-150.The explanation of these parameters are given below:

1. Throughput Analysis

The proposed algorithm has high throughput as compared to other algorithms. The high throughput achieved through optimal bandwidth utilization, minimum route breakage and stable and load balanced cluster structure. High throughput confines the better data handling capability and traffic efficiency. CHAPSOGWO-RL algorithm attains up to 560 kbps throughput, which is higher than other algorithms under all node densities.

2. Delay Analysis

The proposed algorithm minimizes the routing delay because of faster convergence using chaotic functions and intelligent route selection over time. The delay increases slightly with node density but it remains the lowest among all compared algorithms that improves the performance also.

3. Overhead Analysis

The overhead is low for proposed algorithm CHAPSOGWO-RL as compared to other algorithms. Low Overhead shows that the network has better stability under congestion areas, successful routing decisions through RL and having efficient cluster head selection. This defines the robustness of the proposed algorithm in dense environments.

4. Packet Loss Ratio Analysis

The proposed algorithm has the lowest packet loss as compared to other algorithms because of hybrid PSO-GWO confirms stability in fast topology changes, Reinforcement learning fines paths with frequent link failure and Chaotic function prevents local stagnation.

The comparison of all Parameters of proposed algorithm is compared with other algorithms shown below tables:

Table 3: Throughput Analysis

Number of Vehicles	Proposed Algorithm (yellow)	K Means Clustering(green)	ROAONC (blue)	Genetic Algorithm(red)
10	70	68	66	64
15	74	72	70	66
20	78	76	72	68
25	82	80	74	70
30	86	84	76	72
35	90	88	80	74
40	92	90	84	76

Table 4: Delay Analysis

Number of Vehicles	Proposed Algorithm (yellow)	K Means Clustering(green)	ROAONC (blue)	Genetic Algorithm(red)
10	13.0	14.0	18.0	30.0
15	14.0	17.0	20.0	28.0
20	15.0	19.5	21.0	32.0
25	12.5	18.0	17.0	30.0
30	11.5	17.0	15.0	32.0
35	13.0	18.0	16.0	34.0
40	13.5	19.0	16.5	36.0

Table 5: Overhead Analysis

Number of Vehicles	Proposed Algorithm (yellow)	K Means Clustering(green)	ROAONC (blue)	Genetic Algorithm(red)
10	31.0	33.0	48.0	55.0
15	32.5	35.0	44.5	58.0
20	33.0	36.5	42.0	56.0
25	35.5	38.0	41.0	54.0
30	34.0	39.5	40.0	56.0
35	33.0	41.0	42.5	57.5
40	32.0	43.0	44.5	59.0

Table 6: Packet-loss Analysis

Number of Vehicles	Proposed Algorithm (yellow)	K Means Clustering(green)	ROAONC (blue)	Genetic Algorithm(red)
10	63.0	66.0	89.0	96.0
15	60.0	60.0	85.0	92.0
20	57.0	61.0	81.0	88.0
25	54.0	62.0	78.0	85.0
30	52.0	63.5	75.0	85.0
35	49.0	58.0	73.0	84.0
40	47.0	50.0	72.0	83.0

The performance of the proposed algorithm is evaluated using simulation on NS2(version 2.35) by using the network topology as shown in figure 3. with 40 nodes. We have implemented the agents with new packet format where the network animator (NAM) shows the vehicles, RSU and their data passing technique.

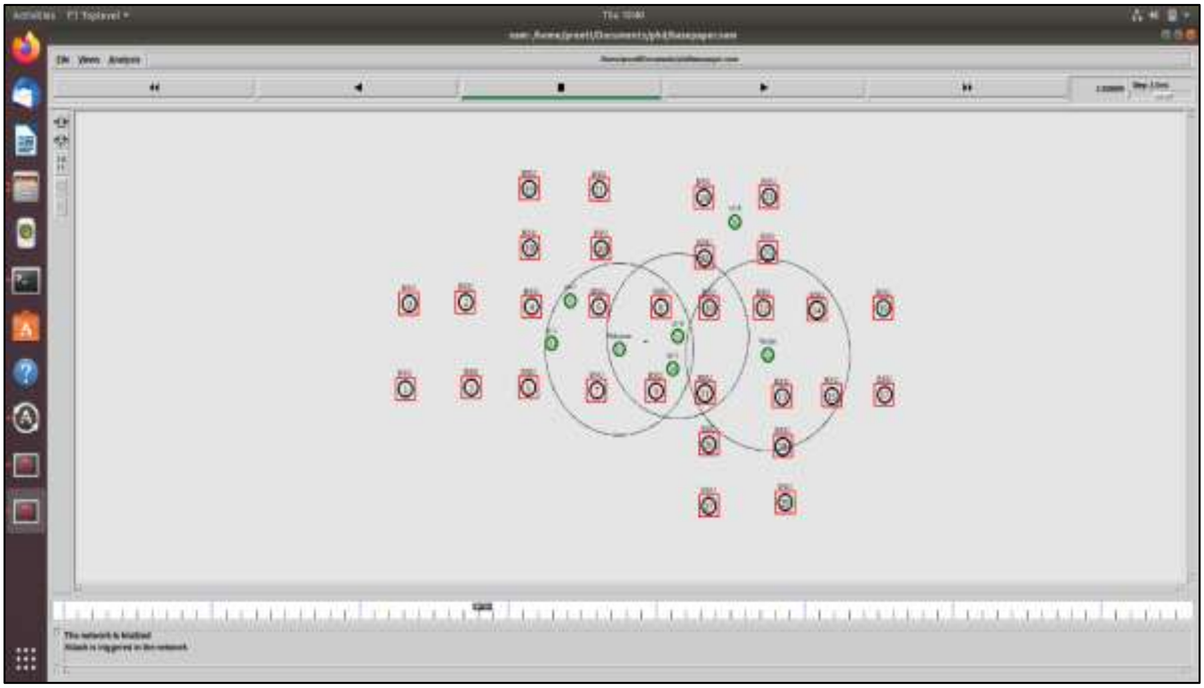

Figure 6: Network Topology

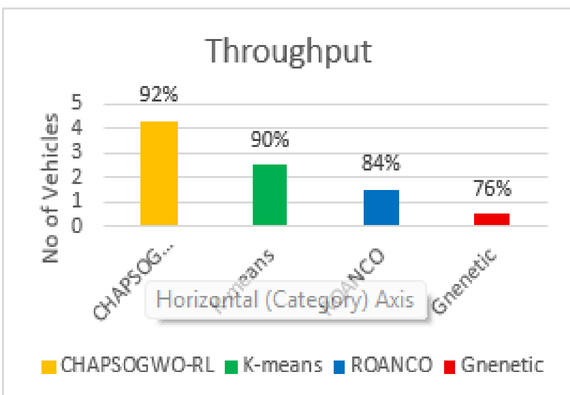

Figure 7. Throughput analysis

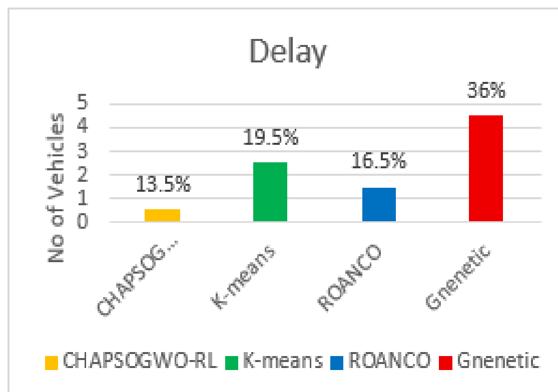

Figure 8. Delay analysis

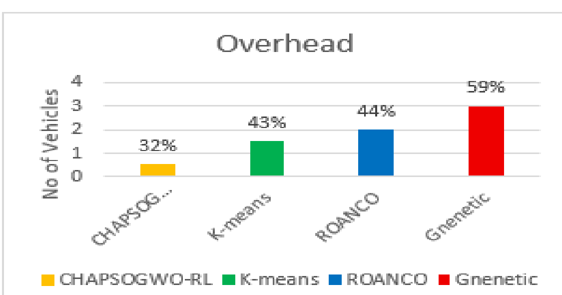

Figure 9. Overhead analysis

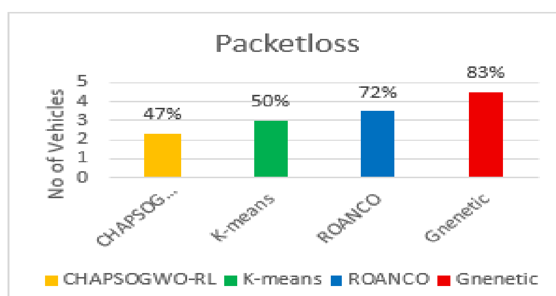

Figure 10. Packet loss analysis

8.Conclusion

This study combines Chaos-driven Adaptive hybrid PSO_GWO with Reinforcement Learning to create a unique VANET optimization framework called CHAPSOGWO-RL. Major VANET issues including frequent link failure, erratic connection, high mobility, and dynamic topology changes are effectively addressed by the suggested hybrid paradigm. The protocol strikes a better balance between optimality and flexibility by combining the global exploration capabilities of PSO, the powerful exploitation capability of GWO, Chaotic augmentation for quick convergence, and RL-based reward learning for routing decisions.

In terms of Delay, throughput, packet-loss and overhead analysis, experimental data shows that CHAPSOGWO-RL routinely beats cutting edge protocols such as ROANCO, K-means Clustering, and GA based routing. These enhancements show improved bandwidth usage, reduced communication overhead, and increased route reliability. As a result, CHAPSOGWO-RL turns out to be a very reliable, scalable, and intelligent routing solution that can support vital VANET applications including traffic management, emergency response, and collision avoidance in smart transportation systems.

Future Work

Despite the encouraging outcomes of suggested CHAPSOGWO-RL technique, there are still chances to further this research in integration with edge computing and 5G/6G, Energy efficient optimization, Cross layer Optimization, MAC scheduling, Security aware routing, deep reinforcement learning, real world simulation etc. This research founds an intelligent, chaos hybrid optimization approach that releases new directions in AI-driven autonomous and robust VANET routing, supportive future smart mobility systems.

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