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Proposing a Hybrid Topological Organization for Non-Misbehaving Nodes with Optimal Path Selection Using Game-Theoretic Approach

[1]Kanmani S and [2]M. Murali

[1]*Department of Computer Science and Engineering, SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu, India*
[2]*Department of Computing Technologies, SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu, India*

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Corresponding Author:
Kanmani S
Department of Computer Science and Engineering, SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu, India
Email: kanmanis@srmist.edu.in

Abstract: In dynamic communication networks, improvement of energy efficiency is one of the major challenges for reliable communication. By considering this challenge, we focus to develop the topology of the network. In this study, we design a hybrid star-mesh topology for minimizing the latency as well as energy consumption of the network. In the hybrid network topology, the Ad-Hoc On-Demand Multipath Distance Vector (AOMDV) routing protocol is used to establish multiple paths between source and destination. Among the multiple paths, the optimal path is chosen using Chimp Optimization Algorithm (ChOA) when the routing path loses its energy level. The optimal path selection leads to enhancing the energy efficiency of the network. Simulation results discuss the superior performance of the proposed scheme in terms of delivery ratio, energy consumption, delay, and throughput by 7% on aggregate.

Keywords: Dynamic Communication Network, Hybrid Topology, AOMDV Routing Protocol and Chimp Optimization Algorithm (ChOA)

Introduction

In recent years, modeling applications of game theory in a selfish environment has become more difficult. If the existing strategy is not offering a desired optimal solution or path, to build a different strategy for competing among players, game theory strategic models are used for the decision-making process. Networking elements like flow management, bandwidth allocation, and routing have been incorporated into modern game-theoretic models to highlight the significance of game theory and networks functioning together. The Nash equilibria of particular games that can resolve networking concepts successfully have been the focus of research.

With all the results from these techniques, the area for optimization had a significant gap. In terms of networking concepts, topology design is not optimized. Hence, the price of anarchy (how agent behavior leads to a reduction in efficiency) and the price of stability (highest objectively desirable level-k equilibrium value) should be incorporated into the network game-theoretic model in order to satisfy the Nash equilibria-enforced optimum.

Networks of communication are constantly improving in terms of both quantity and quality. As the number of network-capable devices increases, so does the need for strong connections, such as those with high bandwidth and low latency. Additionally, the essential requirement for constant availability to ensure the proper operation of mission- or safety-critical frameworks creates the need for robust and adaptable communication frameworks (Du and Zhou, 2009; Dinh *et al*., 2009; Xie *et al*., 2008). In addition to their many advantages, communication networks have several drawbacks, such as lack of centralized control, bandwidth limitations, power supply restrictions, resource accessibility restrictions, routing overhead, etc.

At the time of communication, nodes can move to any place with no limitations. The nodes utilized in the network are chiefly imperative with energy power, speed, data transmission, and limit. Among these imperatives energy is a significant resource, so it assumes an indispensable part and to be tended to basically. Since energy can't be supplanted or making substitutes is troublesome while communication happens. So, it should be utilized as ideally as could be expected, and energy conservation gives regard consideration by analysts today (Feng *et al*., 2012; Sukumaran *et al.*, 2013).

Besides, the network needs to work for a significant time period, yet the nodes are powered by batteries, so the accessible energy resources limit their general activity.

The significant objective of routing protocol for dynamic networks isn't just to forward data from a source to a destination, yet additionally to improve the lifetime of the network. This can be accomplished by utilizing energy-effective routing protocols (de Oliveira Schmidt and Trentin, 2008; Lavanya *et al*., 2017). Contingent upon the applications utilized, various structures and plans have been applied in dynamic networks. The execution of a routing protocol relies upon the structure and network design and this is a vital component of dynamic networks. Nonetheless, the activity of the protocol can influence the amount of energy used to transmit data. Thus, to enhance the energy efficiency and lifetime of the network, the resulting contributions are listed:

- For enhancing the performance of dynamic communication network, hybrid star-mesh topology is presented
- In the hybrid network topology, multipath is established between source and destination using the AOMDV routing protocol
- To enhance the energy efficiency of the network, an optimal path is selected when the routing path loses its energy level. The ChOA algorithm is described for choosing the best path
- The proposed scheme performance is evaluated by analyzing the delivery ratio, energy efficiency, network lifetime, and throughput

Youssef *et al*. (2010) introduced a dynamic hybrid topology-based Wavelength Division Multiplexing (WDM) mesh network on an integrated traffic network. In this approach, they take into account the issue of integrated dynamic design in a practical WDM mesh network. In this approach, the bandwidth for a single wavelength was large. For this approach, they created a combination of current light trees and light paths with virtual topography, using a sub-wavelength distribution between the transport needs of Unicast and Multicast. In this approach, the authors had to upgrade WDM resources with existing Unicast and Multicast requests. WDM improves layer capacity and efficiently supports higher traffic demands. Then the effectiveness of the proposed system was analyzed. To show that the simulations are valid, numerous WDM mesh networks are used and capable with relatively large networks.

Hussein and Dahnil (2017) introduced an AD-HOC upgrade path chosen with a new hybrid technique to reduce power consumption in mobile networks. With this strategy, routing protocols advanced from choosing the fewest possible hops to taking into account other factors influencing path selections. In this approach, as the distance between each node increases, the transmission power increases. Additionally, after discovering all potential paths, the authors developed a novel method for enhancing path selection by combining ant-colony optimization and the Lion optimization algorithm. Additionally, each node's performance measures and energy efficiency are enhanced by this method. This study suggests a QoS-compatible routing strategy for the MANET that satisfies power constraints and lengthens network lifetime.

Shi (2021) introduced combining the Viterbi algorithm and the Bayesian algorithm into a Network Topology Structure optimizing System. In this approach, a method was proposed to improve the spatial structure of the layer under the communication network. The Viterbi method was used to initially optimize the path in regions with poor network conditions. Subsequently, they used the network nodes in the path were optimized using the Bayes recommendation method for fair flow distribution. The dual scheduling algorithm of the enhanced Viterbi algorithm was used to realize key and standby path scheduling. Then the Bayesian Recommendation Algorithm was used to upgrade network components based on the average value.

Zuo *et al*. (2013) introduced an industrial wireless mesh network used for a hybrid multi-path routing algorithm. In this approach, a hybrid multi-path routing algorithm for industrial wireless mesh networks was proposed. The proposed approach is used to improve the reliability and stability of data transmission and to effectively handle connection failures. In this approach, the proposed algorithm adopted the upgraded Dijkstra algorithm. For this approach, the authors introduced different virtual pheromones to realize pheromone diffusion and renewal. In this way, several avenues based on the ant colony optimization algorithm were searched. Connection failures were handled using a path maintenance mechanism. The simulation results demonstrated that the proposed algorithm outperforms traditional algorithms.

Khan *et al*. (2018) introduced routing protocols of dynamic routing on ad hoc networks by using topology. In this approach, the authors experimented with establishing efficient and robust communication between Unmanned Aerial Vehicle (UAVs). The authors focused on the routing protocols of the proposed approach, performance, end-to-end delay, and network load. The authors provided a brief overview of the routing protocols of FANETs. With the pros and cons of each protocol, the authors have provided features for exchanging information. The proposed approach assists network engineers in selecting FANET routing protocols.

Hamsaveni and Choudhary (2021) introduced using a Multi-Objective Hunger Locust Optimization algorithm (MO-HLO) of multi-objective optimization algorithm for routing path selection and bandwidth allocation for dynamic WTM networks. In this approach, the authors proposed a novel multi-objective optimization algorithm.

The authors used an improved model of MO-HLO. In this approach, the authors analyzed the traffic level on a network path and the availability of wavelength at each time. In the data, the upgrade selected the best in the overall feature set of the WDM arrangement. The MO-HLO algorithm created a cluster that separates the routing path from the traffic limit. The authors concluded that the proposed optimization algorithm reduces the time problem and data packet loss.

Kojić *et al*. (2012) introduced a hybrid routing protocol for Wireless Mesh Networks (WMN) based on neural networks. In this approach, the authors discussed changes in network topology and connection quality. In this approach, the authors classified the hybrid routing protocol using the new routing protocol for WMN. For this approach, the proposed solution avoids flooding and creates a new routing metric. In this approach, the authors used Neural Networks (NNs). In addition, the authors used multi-criteria optimization to reduce the probability of new routing metric delays. From this approach, the authors found that the protocol was suitable for dynamic network topology and actual network environments.

Zheng *et al*. (2021) introduced analyzing space-air-ground integrated networks (SAGINs) using the Ant Colony Optimization (ACO) based cross-layer routing algorithm. In this approach, important parameters affecting the performance of SAGINs were analyzed. In this approach, a Weiner forecast was adopted to meet time-varying requirements and to obtain rated channel information. In this approach, an ACO-based cross-layer routing algorithm for SAGINs was proposed. In this approach, the proposed algorithm had a higher pocket transmission rate and a slight increase in pocket transmission delay compared to the classic AntHocNet algorithm.

Price of Anarchy (PoA) and Nash equilibrium game theory (Chandan *et al*., 2019; Wu *et al*., 2023) analysis is provided to identify network nodes that are selfish, which will improve the effectiveness of nodes' communication inside a dynamic communication network. This metric helps in finding selfish behavior in the dynamic communication environment. In game theory, PoA is investigated at the Nash equilibrium for repeated games. Based on the PoA value (Belov *et al*., 2022), which must be greater than one, selfish nodes are recognized and eliminated from the network. After the removal of selfish nodes, resources are distributed to normal nodes using the Capacitated Selfish Resource Allocation (CSRA) game (Roughgarden, 2015; Cominetti *et al*., 2021; Colini-Baldeschi *et al*., 2020). For resource allocation, we implemented the CSRA technique.

The application of the equilibrium strategy maximizes each player's personal gains. If each of these players changes their strategy independently, they will all lose (Colini-Baldeschi *et al*., 2019). When each player adopts a plan and when no player can profit from changing their own strategy while the other players' approach remains the same, Nash equilibrium is determined by the available strategic choices and associated payoffs (Takalloo and Kwon, 2020). A payment matrix between two nodes is created. The payoff of each player is assessed based on the nodes' remaining energy, or E_{res}. The remaining energy represents the node's payoff E_{res} if the packet of one node is forwarded by another node (Wu *et al*., 2021). When a node forwards another node's data packet, the node incurs energy loss or E_{loss}. The payoff of both nodes is regarded as E_{res}-E_{loss} if player 1 and player 2 are advancing packets to one another (Paccagnan *et al*., 2021).

Liao *et al*. (2023) proposed three different aerodynamic layout designs for different design variables such as size, shape, and topology design. From the perspective of aircraft design, aerodynamic configuration plays a vital role to support the flight performance and flight quality of aircraft. The design variables and topology structure parameters together layered the concept of Artificial Intelligent Topology Design (AITD) for aerodynamic configuration design. The current artificial intelligence may need to be improved in order to learn from a limited number of samples while supporting topology optimization. As more evaluations are performed using the RANS CFD solver, the computational cost rises. While this is the case, conventional AI needs a large number of samples to increase model accuracy.

A new topology design optimization framework with joint human-machine design decisions was described by Ha and Carstensen (2023). They introduced Human-Informed Topology Optimization (hitop) algorithm. The new hitop approach uses standard density-based compliance optimization as the backbone of the algorithm.

Chimp Optimization Algorithm Based Optimal Path Selection with Hybrid Topology

Overview

To enhance the performance of dynamic communication networks in terms of energy efficiency, delivery ratio, and throughput, an efficient network topology is to be designed. As the star and mesh topologies provide low power characteristics and minimal latency respectively, hybrid star-mesh topology is presented in this study. Following the creation of the network topology, the AOMDV routing protocol is used to build a number of routing pathways between the source node and the destination node. A path may lose its link quality as a result of the volume of transmissions, causing the source node to select an alternative ideal path. This study presents the Chimp optimization algorithm (ChOA) for selecting the best path. Figure 1 demonstrates the workflow of the proposed approach.

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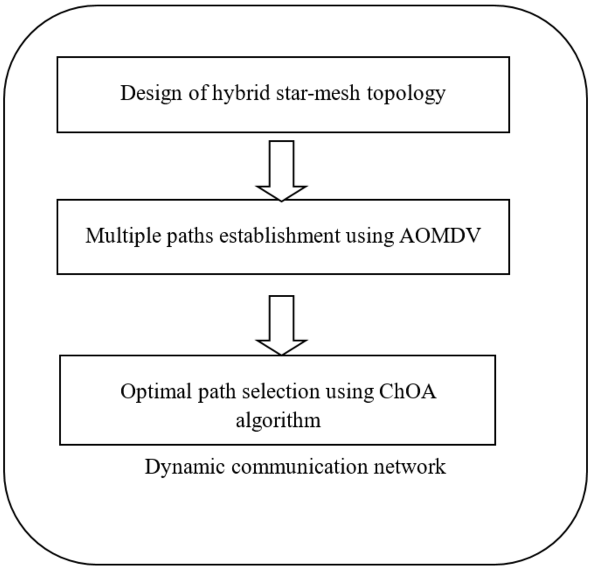

Fig. 1: Workflow diagram of the proposed approach

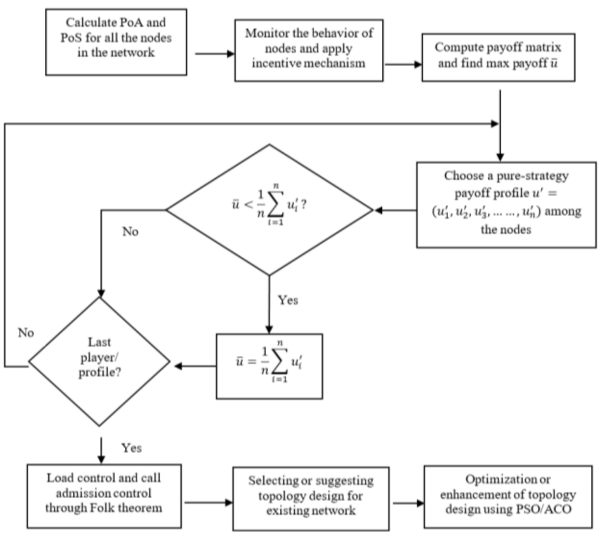

Fig. 2: Workflow diagram of topology design and optimization for non-misbehaving nodes in a network

The workflow of how the topology design and optimization work with hand in hand is showcased in Fig. 2. Initially the values of PoA and PoS are computed and selfish behavior in the participating nodes is identified in the network. Then the payoff computation will take place for all the non-misbehaving nodes which handles the strategic complementarities that exist between nodes. Finally, topology design and optimization will fall in place to arrange the nodes in a proper order to broadcast or receive packets from other nodes in the network. The next section discusses more about the hybrid topology designed for all the participating nodes.

Materials and Methods

Hybrid Network Topology

In this study, the network topology of dynamic communication is designed using star-mesh hybrid topology. In star topology, the nodes are arranged in the structure of a star where the nodes couldn't communicate with each other but they can only communicate with the base station. This topology consumes less energy as the nodes don't concentrate on forwarding and routing. Likewise, in mesh topology, all the nodes form a multi-hop network where each node communicates with each other and also communicates with the base station. Besides, each node in the topology has redundant paths to the base station.

The drawback of star topology is the absence of communication redundancy. Thus, a node cannot forward the data via an alternate path if the communication link between the node and base station is interfered with by any object or another signal with the same frequency. Besides, as each node should be in the communication range of the base station, more base stations might have to be utilized in the topology. Likewise, the drawback of mesh topology is that it consumes more energy for routing. Compared to a star topology, a lifetime of nodes in mesh topology is not sufficient.

By combining these topologies, the dynamic communication network can be benefited from the metrics of star and mesh topology. So, in this study, the topology of the network is designed using the star-mesh hybrid topology. Figure 3 shows the structure of the star-mesh hybrid topology. As illustrated in the figure, a router node from the mesh topology is the centre of any star topology. In this topology, each node can be in the communication range of more than one router node. Besides, it has more redundant paths. As the star-mesh hybrid topology utilizes the metrics of mesh topology like fault tolerance and extended range and that of star topology like less power consumption, the routing performance of the dynamic communication network will be improved.

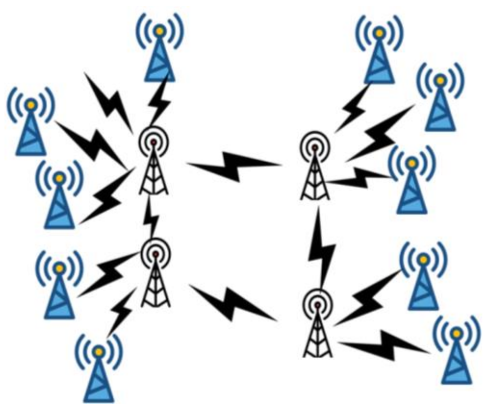

Fig. 3: The structure of the star-mesh hybrid topology

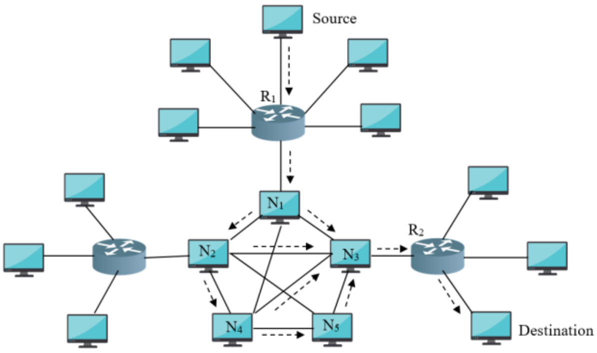

Fig. 4: An instance of multiple paths establishment between the source and destination

Multiple Paths Generation Using AOMDV

At first, a number of paths are established between the source and destination in the hybrid network topology. In this study, the AOMDV routing protocol is applied for the establishment of a number of paths. The source node transmits route requests, designated as RREQ, to its neighbouring nodes throughout the operation of AOMDV. By receiving RREQ, a path is formed towards the destination by the nodes. The routing path is updated in the routing table of each node. The destination node starts to forward route replies denoted as RREPs to RREQs received from various intermediate nodes. At final, data transmission is initiated from the source node to the destination via multiple paths. Figure 4 shows an instance of multiple paths establishment between the source and destination. The figure illustrates the multiple routing paths such as source-R_1-N_1-N_3-R_2-Destination, source-R_1-N_1- N_2 -N_3- R_2-Destination, source-R_1-N_1- N_2 – N_4-N_3- R_2-Destination and source-R_1-N_1- N_2 – N_4- N_5 -N_3- R_2-Destination.

The energy of the routing path may lose because the number of transmissions increases. Additionally, as energy is lost from the routing pathways, packet loss also rises. The success rate of data transmission is also impacted. An ideal routing path, excluding the failure path, is selected to address these issues. In this study, we present the ChOA path selection method. The next section provides a description of optimal path selection using the ChOA algorithm.

Optimal Path Selection Using ChOA Algorithm

This section uses the ChOA algorithm to find the best routing path between the source and the destination. In this algorithm, chimps, often known as chimpanzees, are an African species of big ape. Chimpanzees' Brain-to-Body Ratio (BBR) resembles that of humans the most. Therefore, if a mammal has a higher BBR, it is assumed that they are similarly intelligent to humans. Given that both chimpanzees and humans are descended from hominoid creatures that existed millions of years ago, it is possible that their DNA is related. Because these chimpanzees generally live in a fission-fusion society, the size of the colony can alter as time passes and individuals move about the habitat. Each chimpanzee group alone tries to locate the hunt space in the colony using its own method. Chimpanzees in each group vary considerably in terms of intelligence and skill, yet they are all carrying out their roles as members of the colony as a whole. Every person has skills that can be useful in a certain situation.

Additionally, there are four different types of chimps in the colony and they are as follows:

- Drivers: They do not attempt to catch the victim; they merely pursue it
- Barriers: To block the movement of the prey, they perch themselves in a tree
- Chasers: They chase the prey swiftly in order to hunt it
- Attackers: They anticipate the prey's escape route in order to direct it downward into the lower refuge or back toward the pursuers

In general, the chimp's hunting process is partitioned into two fundamental stages: "Exploration" which comprises driving, impeding, and pursuing the prey, and "Exploitation" which comprises assaulting the prey.

The following is a description of how the ChOA algorithm chooses the best path.

Initialization: In ChOA, the position of the chimps represents the position of the solutions in the search space. In this study, the routing paths between the source and destination are considered as the solutions. The population of the solutions is initialized as follows:

$$P_N = \{y_1, y_2, \ldots\ldots, y_N\} \tag{1}$$

where, y_N represents the N^{th} result or the location of the chimp and it represents the routing path R_N.

Fitness calculation: Utilising the routing paths' residual energy and latency, each solution's fitness is calculated. The total delay (D_{Total}) and residual energy (E_{Total}) of the routing paths are defined as follows:

$$D_{Total}(l) = \sum_{k=1}^{m} d_{kl} \tag{2}$$

$$E_{Total}(l) = \sum_{k=1}^{m} e_{kl} \tag{3}$$

where, k denotes the m number of nodes in the l^{th} routing path, d_{kl} denotes the delay of *a* k^{th} node in the l^{th} routing path and e_{kl} denotes the residual energy of *the* k^{th} node in the l^{th} routing path.

Using (2) and (3), the fitness of the N^{th} solution is estimated as follows:

$$Fit(N) = \begin{cases} Max\left(\dfrac{1}{D_{Total}(l)}\right) & \forall l \\ Max\left(E_{Total}(l)\right) & \forall l \end{cases} \tag{4}$$

The solution or routing path with the highest fitness is selected as the optimal path, according to (4). The position of the ideal path in this method indicates where the prey is located. If the target fitness is not achieved, the solution is revised using chimpanzees' hunting habits.

Update the solution: The phases that follow provide explanations of how chimps hunt or how to update a solution.

Driving and Chasing the Prey: Eqs (5-6) define the mathematical equation of driving and chasing the prey:

$$z = \left| y_{prey}(t) * c - y_{chimp}(t) * n \right| \tag{5}$$

$$y_{chimp}(t+1) = y_{prey}(t) - b * z \tag{6}$$

where, t stands for the current iteration, the position of prey is denoted as y_{prey}, and the position of chimp is represented as y_{chimp}. b, c, and n denote the coefficient vectors and are determined as follows:

$$b = 2 * f * rand_1 - f \tag{7}$$

$$c = 2 * rand_2 \tag{8}$$

$$n = Chaotic\_value \tag{9}$$

where, $rand_1$ and $rand_2$ denote the random vectors within [0, 1], and f stands for the coefficient vector that decreases nonlinearly from 2.5-0 through the iterative procedure. The chaotic vector n represents the influence of chimps' sexual desire on the hunting process. Its estimation is based on various chaotic maps.

Exploration or attacking stage: Driver, barrier, and chaser chimps assist the attacker chimps in hunting the victim during the hunting process. Typically, the chimps who are attacking carry out the act of hunting. In the mathematical formula, the best answer, or the initial attacker, driver, barrier, and chaser, is used to determine the position of the prey (Durand *et al*., 2019; Ewerhart, 2020). The top four solutions have been found and are saved. The placements of other chimpanzees are then updated based on where the best ones are located. This can be defined in Eqs. (10-12):

$$\begin{aligned} Z_{Attacker} &= \left| y_{Attacker} * c_1 - y * n_1 \right| \\ Z_{Barrier} &= \left| y_{Barrier} * c_2 - y * n_2 \right| \\ Z_{Chaser} &= \left| y_{Chaser} * c_3 - y * n_3 \right| \\ Z_{Driver} &= \left| y_{Driver} * c_4 - y * n_4 \right| \end{aligned} \tag{10}$$

$$\begin{aligned} y_1 &= y_{Attacker} - Z_{Attacker} * b_1 \\ y_2 &= y_{Barrier} - Z_{Barrier} * b_2 \\ y_3 &= y_{Chaser} - Z_{Chaser} * b_3 \\ y_2 &= y_{Driver} - Z_{Driver} * b_4 \end{aligned} \tag{11}$$

$$y(t+1) = \frac{y_1 + y_2 + y_3 + y_4}{4} \tag{12}$$

Prey attacking stage: The chimps will assault the victim at this point, stopping the hunting process because the animal has stopped moving. In this stage's mathematical expression, the value of the coefficient f should be reduced. Aside from that, the range of b is also decreased by lowering the value of f. In particular, the range of b is altered between [-2*f*, 2*f*], where the f value is reduced from 2.5-0 during iteration. When the value of b falls between [-1, 1], a chimpanzee selects between its current location and the location of its prey for its nest. If $|b|<1$, the chimps are compelled to attack the prey.

Exploration stage: The chimpanzees are separated from their prey during this stage and made to look for the best prey. The chimpanzees are compelled to diverge from prey if the value of b is larger than 1 or less than -1, according to the mathematical expression of divergence behavior. The global search algorithm is made possible by this technique. Finding the best prey $|b| >1$ is placed upon the chimpanzees. Additionally, inside the range [0, 2], the c factor is utilized to prevent local minima.

Social motivation: At this point, chimpanzees' social incentive causes them to abdicate their hunting responsibilities. They then make a powerful chaotic endeavor to acquire meat. Chimpanzees' chaotic behavior during the last stage helps to offset the two problems of capture in local optima and the slow pace of convergence when dealing with high-dimensional problems. The use of chaotic maps has improved ChOA's performance. These chaotic maps are cycles with deterministic properties that also exhibit random behavior. We anticipate that there will be a 50% chance of choosing either the chaotic model or the standard updating position approach to update the chimpanzees' position in order to show this concurrent behavior. Equation 13, which defines the behavior's mathematical expression:

$$y_{Chimp}(t+1) = \begin{cases} y_{prey}(t) - b * z & if\ \eta < 0.5 \\ Chaotic\_value & if\ \eta > 0.5 \end{cases} \tag{13}$$

where, η represents a random number between [0, 1].

Termination: Up until the ideal routing path between source and destination is found, the solutions are modified based on how chimpanzees hunt. Once the answer is found, the algorithm will be stopped.

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Algorithm: Optimal path selection using the ChOA algorithm

Input: Routing paths (R_N), coefficient factors b, f, n, and c.
Output: Optimal routing path

1. Initialize the population of solutions P_N and coefficient factors
2. Estimate each chimp's position
3. Split chimps into random groups.
4. Evaluate the fitness of each chimp
5. Store the four best search agents $_{\text{attacker}}$, y_{Chaser}, y_{Barrier}, and y_{Driver}
6. **While** (Max No.of iterations > t)
7. **For** every chimp
8. Extract the group of chimps
9. Update f, c, and n using Chimp's group strategy
10. Calculate b and z using f, c, and n.
11. **End for**
12. **For** every search chimp
13. **If** η<0.5
    If∣b∣<1
    Update the current position of the search agent using (6)
    Else if∣b∣>1
    Choose a random search agent
14. **Else if** η>0.5
    Update the current position of the search agent using (13)
15. **End if**
16. **End for**
17. Update n, b, c, and f
18. Update y_{Attacker}, y_{chaser}, y_{Barrier} and y_{Driver}
19. t=t+1
20. End while
21. **Return** y_{Attacker}
22. Steps 2-21 are continued until obtaining the optimal solution.
23. Terminate the algorithm once the optimal solution is obtained

Results and Discussion

The proposed scheme is simulated using Graphical Network System 3 (GNS3) in the platform of Python with the Windows 10 operating system and is implemented on a 2 GHz dual-core PC machine with 4GB of main memory running the 64-bit. Initially, the simulation process started with the selection of various hybrid topology design which suit the current network as shown in Fig. 5. Added to that the congestion window was also monitored in GNS3 for two sub-flows as represented in Fig. 6 where we included selfish nodes and Fig. 7 where we prevented selfish nodes. This ensures the reduction in congestion in Fig. 7 when compared to Fig. 6.

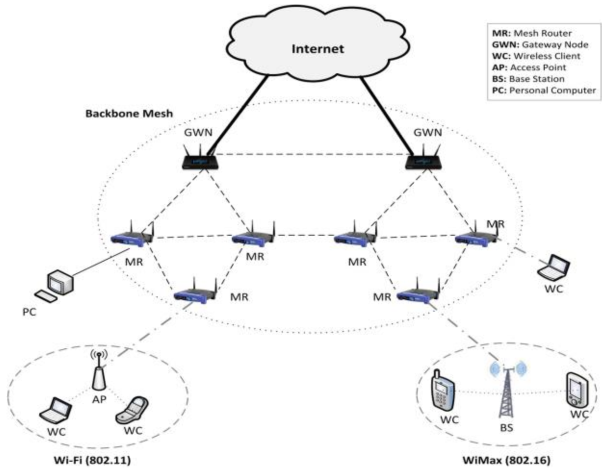

Fig. 5: Model of hybrid topology design in graphical network system 3

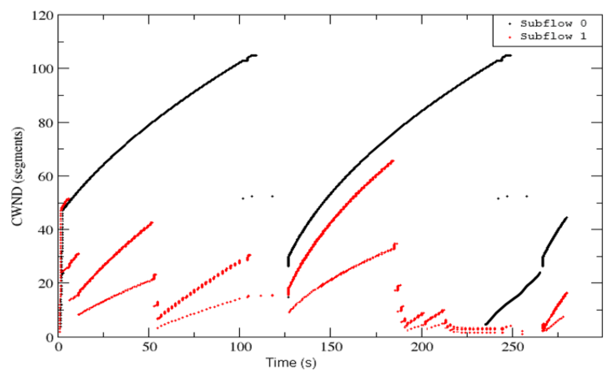

Fig. 6: Congestion window for two sub-flows involving non-misbehaving nodes in the network

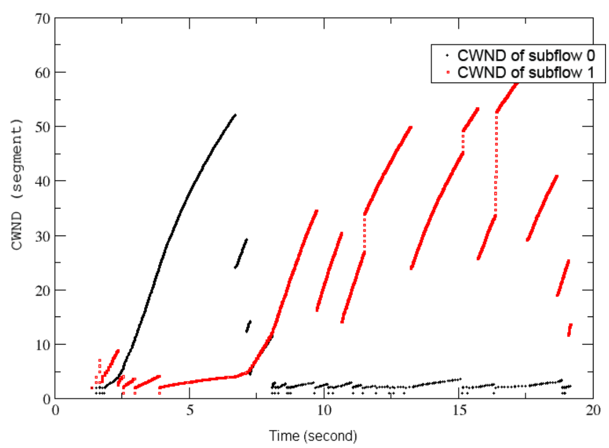

Fig. 7: Congestion window for two sub-flows exempting non-misbehaving nodes in the network

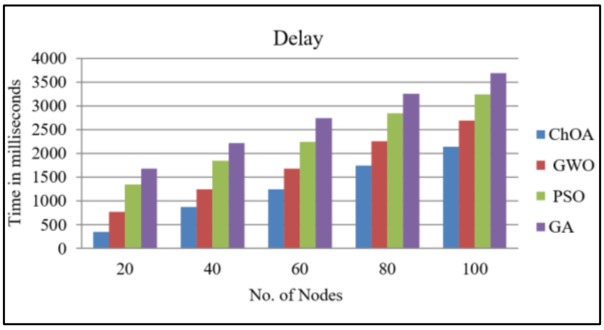

Fig. 8: Number of nodes vs delay

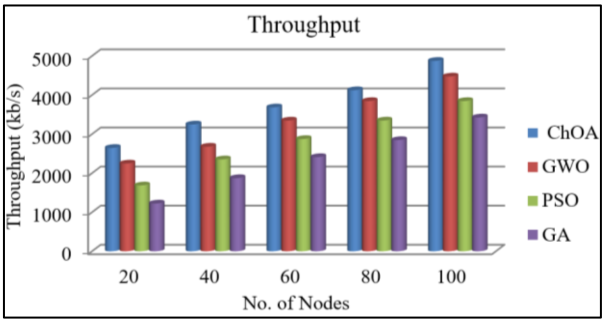

Fig. 9: Number of nodes vs throughput

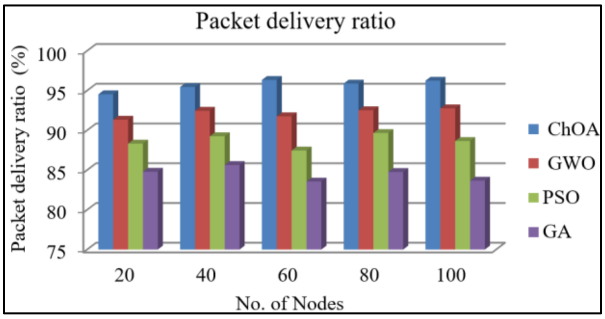

Fig. 10: Number of nodes vs delivery ratio

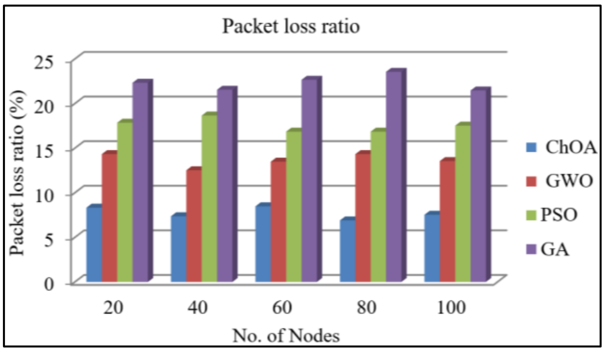

Fig. 11: Number of nodes vs packet loss ratio

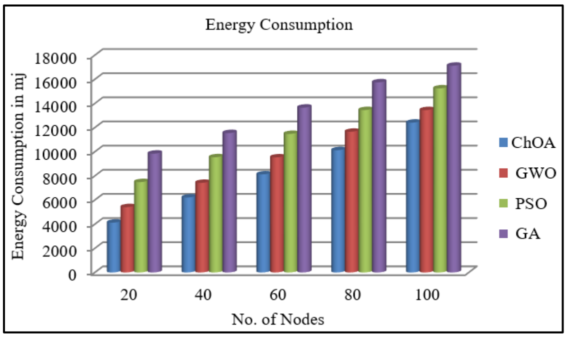

Fig. 12: Number of nodes vs energy consumption

Performance Analysis

In this section, the performance of different algorithms based on optimal path selection in hybrid network topology is evaluated with the support of the following metrics delay, throughput, delivery ratio, packet loss ratio, energy consumption, and network lifetime. Besides, ChOA algorithm-based optimal path selection is compared with the existing algorithms Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). Figure 8 shows the delay of different algorithms-based dynamic communication networks for varying numbers of nodes. As the searchability of the ChOA algorithm is better than the existing algorithms, the accuracy of optimal solution selection is improved. Thus, the delay of the based dynamic communication network is reduced to 23, 45 and 53% than that of GWO, PSO, and GA-based dynamic communication networks. The comparison of the throughput of different algorithms is illustrated in Fig. 9. The optimal path is selected using ChOA when the path loses its energy so that the data is continued seamlessly. It leads to an increase in the throughput of the network. Namely, compared to GWO, PSO, and GA-based dynamic communication networks, the ChOA based dynamic communication network is improved to 12, 32, and 58% respectively.

Figure 10 illustrates the comparison of the delivery ratio of different algorithms based on dynamic communication networks. As illustrated in the figure, the proposed dynamic communication network attains 96% of the delivery ratio at 100 numbers of nodes while the existing GWO, PSO, and GA-based dynamic communication network obtain 92, 88, and 83% of delivery ratios respectively at 100 numbers of nodes. The analysis of the packet loss ratio of the network is illustrated in Fig. 11. Compared to GWO, PSO, and GA, the packet loss ratio of ChOA is reduced to 43, 55, and 63% respectively. As depicted in Fig. 12, the energy consumption of the network is increased when the number of nodes increases. However, the energy consumption of the ChOA-based dynamic communication network is reduced to 14, 28, and 39% more than that of GWO, PSO, and GA based dynamic communication networks.

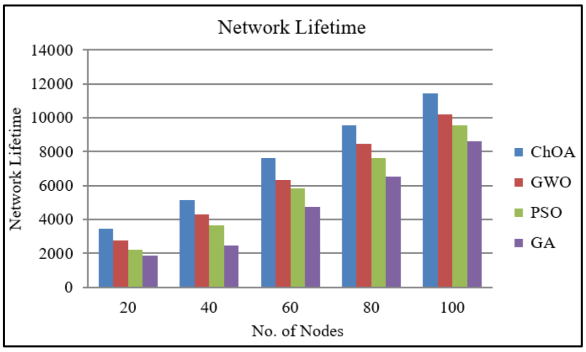

Fig. 13: Number of nodes vs network lifetime

Figure 13 depicts the network lifetime of the dynamic communication network for a varying number of nodes. Compared to GWO, PSO, and GA-based dynamic communication networks, 16, 29, and 54% respectively.

Conclusion

To enhance the energy efficiency of the dynamic communication network, a hybrid network topology has been developed and an optimal routing path has been selected using the ChOA algorithm. At first, the network topology has been developed by combining the star and mesh topology. This hybrid star-mesh network topology has led to minimizing the latency of the network. In the hybrid network topology, multiple paths have been established between the source and destination using the AOMDV routing protocol. Among the multiple paths, an optimal path has been chosen using the ChOA algorithm when the routing path loses its energy level. The results of the article depicted that the energy efficiency of the ChOA based path selection is increased to 7% than that of existing algorithms.

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Author's Contributions

Kanmani S: Conception and design, acquisition of data, analysis and interpretation of data, drafted the article.

M. Murali: Reviewed article critically for significant intellectual content, gave final approval of the version to be submitted and any revised version.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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