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REALIZATION OF ENERGY EFFICIENT CLUSTERING AND POWER OPTIMIZATION IN VANET – A COMPARATIVE ANALYSIS OF GREY-WOLF, ANTLION AND BACTERIAL COLONY OPTIMIZATION TECHNIQUES

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Abstract:
The present work highlights a comparative, data-driven assessment of three nature-inspired meta-heuristic optimization methods—Grey Wolf Optimization (GWO), Ant Lion Optimization (ALO), and Bacterial Colony Optimization (BCO in minimizing power consumption through optimal cluster formation and selection of cluster-heads (CH) for a VANET system. Simulation study shows that clustering can decrease total network power consumption by 80% as compared to without clustering. BCO results in the lowest power consumption, quicker convergence towards global optima, and more compact clustering structures, especially in dense environment. This study shows BCO as an energy-efficient optimization approach for clustering and routing in VANETs.

Keywords: Energy-efficient clustering, VANET, Grey-Wolf optimization (GWO), Antlion optimization(ALO), Bacterial colony optimization (BCO), Cluster-heads (CH), Dense environment.

1. Introduction

In recent era, dynamic access of computing and communication services are at utmost need due to high- speed data communication, merely possible high-end infrastructure, metro area networking framework. In this regards, Vehicular Ad hoc Network (VANET) fulfils the criteria by utilizing wireless vehicle hosts which can change cells during communication through a process called Hopping. VANET is characterized by multiple vehicular links to reach destination that can result changes in routes, self-configurable, ease in deployment, no need of backbone infrastructure or ruined infrastructure. (Fig S1) This type of wireless communication hence, is drawing immense attention due to dynamic node connections and easy to maintenance. Unfortunately, this type of network faces some constraints including lack of a centralized entity, exposed terminal problem, hidden terminal problem, limited wireless transmission range, ease of snooping on wireless transmissions often called security hazard, packet losses due to transmission errors, mobility-induced route changes, resulting packet losses, battery constraints, potentially frequent network partitions, reliability, survivability, availability, manageability of the network. Another prime obstruction in VANET is short transmission range and the mobility induced dynamic interruption in network topology. Hence, there is question of stable communication link. Routing is treated as one of the most painful factors in this dynamic communication system. In the present work, routing problem is considered and the solution path is well described. There are several techniques to address the routing challenges including node prediction, multi-path routing, trust-based routing, optimized link state routing protocol and clustering. Clustering facilitates grouping of nodes or hosts under one head known as cluster head (CH) where the first communication is made in between CH and nodes, followed by the communication made between CH and base station or sink hub.[1] The simultaneous creation and abolishment of Adhoc network due to random mobility of associated nodes, often cause higher energy consumption. Scalability is another prime issue as the scarcity of this parameter can damage of network's sustainability. Also, due to node mobility, topology changes at a faster rate resulting the distortion in scalability. In this case conventional clustering may be an effective solution to secure and protect the scalability as well as lengthen the life span of the VANET. Intelligent clustering provides scalability, manageability, optimization and load balancing of the network. The grouping of the nodes in a particular cluster is made based on similarities of the nodes. The similarities are based on position, distance between the nodes and bandwidth availability. The cluster size is a function of transmission range and residual energy of the node. Due to distinct clusters, individual CHs are present but the improper load balancing can affect its life span.[2][3]. The role of CH is to form and terminate cluster, topology selection for maintenance, resource allocation and management to cluster members. Additionally, CH monitors the communication inside the cluster and other accessible cluster of networks. CH life span, CH stability, CH change ratio and conversion ratio of cluster member to CH. Hence, selection of CH and effective cluster formation are very vital for effective routing and lowering energy consumption.[3] Clustering is categorized into two classes: 1. Hierarchical and 2. Partitional clustering. In hierarchical clustering, each node is assigned to a cluster and then form a big cluster based on similar types of the cluster as mentioned. Another way of hierarchical clustering is starting with a big cluster and decomposing it into similar types of small clusters. Partitional clustering is to divide a set of nodes into non overlapping clusters without forming nested cluster. The center point of a cluster is designated as the centroid. Initially, each node is assigned to the nearest centroid. After this assignment, the centroids positions are recalculated based on the current groupings, aiming to optimize a specific objective or criterion. k-means clustering is most popular technique for partitional clustering where the value of k is initialized and then that number of similar types of data objects are grouped to form a cluster. After that k value is revised and thus the cluster is optimized but the main challenge of this k-mean clustering is the vulnerability of k value to local optimum convergence as well as reliance on its initial value.[4]

Convergence and attainment of global optima are very much decisive for selecting suitable cluster head (CH) and developing requisite cluster. As stated above, low energy consumption is utmost priority in VANET so node residual energy and node density are associated parameters while selecting CH in energy efficient VANET. CH should be selected as per the distance from BS and residual energy in order to maintain trustworthy, dependable and energy efficient wireless sensor network. Thus, energy management strategy becomes a serious concern while implementing MANET in various applications including environmental monitoring, precision agriculture, Internet of Things (IoT) based wireless sensor network (WSN).[5] In this regard, meta-heuristic algorithm is considered as a competitive agent to solve the convergence and local optima problem. Meta-heuristic algorithm is a sub set of computational method that utilizes a search space to solve a complex problem iteratively. The entire iteration is based on mimicking animal's or human's intelligence. Computational intelligence is one of the most well-versed strategies to solve the routing challenge by clustering mechanism inspired by biological systems. This type of optimization technique can be classified as 1. Local search-based technique and 2. Population based strategy. Another categorization reveals that meta-heuristic search policy is classified as 1. Evolutionary Algorithm (EC), 2. Physical-based algorithm, 3. Chemical Based Algorithm and 4. Human based algorithm and 5. Swarm Intelligence Algorithm (SI). However, local search-based technique places an initial solution of a complex problem and then it improves the solution iteratively by continuous exploration of neighbouring solutions. The iterations will terminate once the process will attain maximum iterations or the solution has reached local optimum value. Simulated annealing, greedy randomized adaptive search (GRAS), variable neighbourhood search strategy (VANS), Iterated Local Search (ILS), VORTEX search and β-hill climbing. EC is one kind of population-based search (PBS) algorithm where a pack (population) of solutions are initially created. stirred by natural selection of biological species to find out the optimal cluster framework to solve routing issues and related power consumption. The algorithm converges through a series of steps such as recombination, mutation and natural selection process. Genetic algorithm (GA), differential evolution (DFE), evolutionary programming (EP), genetic programming (GP), probability-based incremental learning (PBILN) and finally biogeography-based optimization(BBO] [6] Plasma generation optimization (PGO),Ray Optimization (RO), Solar system algorithm(SSA), Gravitational search algorithm (GSA), Brilliard-Search Optimization (BSO) etc. are examples of physical and chemical search algorithm where physical laws and chemical interactions among components are impregnated. Algorithms modelled after getting motivated from human or social behaviours include harmony search, heap-based optimizer, brain storm optimization. This algorithm exemplifies teaching-learning-based optimization, political optimizer, rich optimization algorithm, Ali Baba and the Forty Thieves, Ebola optimization search algorithm, group teaching optimization algorithm, coronavirus herd immunity optimizer, football game-inspired algorithm, arithmetic optimization algorithm, stock exchange trading optimization etc. SI offers communal intelligent comportments from a large number of autonomous individuals (Swarm). It is inspired by the collective attribute of living species in animal kingdom like bird, bee, wolf, frogs, bats etc. This computational technique fosters novel intelligent algorithms to solve complex real-world problems and the novelty lies in searching for food, prey hounding process decided by the local interaction between the members of the group or environmental interaction that is often known as "Stigmergy". This algorithm initiates with a swarm of solutions. The swarm has two groups including leader (Head) and follower. The convergence of the algorithm is realized after the attraction of follower to the leader. If the leader is not suitable, then a hierarchy of leader will be formed and the followers will follow the instructions of the leader to attain the convergence. Simply it can be stated that SI has a constellation of solutions instead of single solution for a specific problem due to its cooperative culture of foraging process of biological species in the nature. It synthesizes the information sharing and mutual learning among the group members. It is a meta-heuristic process that constantly changes search direction for convergence. SI has the strong potential to form an effective cluster with cluster head (CH) and cluster members. The absence of centralized administration (CH) in the overall activity of this intelligent system and enforces distributive control over its performance. Moreover, the overall success of this computational intelligence is not affected by individual failure. There are a club of meta-heuristic algorithms like Particle Swarm Optimization (PSO),Artificial Bee Colony (ABC) algorithm, Firefly Algorithm (FA),Ant Colony Optimization (ACO), Butterfly Optimization Algorithm, Chicken Swarm

Algorithm, Snake optimizer, Antlion optimizer, Elephant herding optimization, Sparrow search algorithm, Horse herd optimization, Dragonfly algorithm, Whale Optimization Algorithm, Rat swarm optimization, Harris Hawks Algorithm Moth-flame optimization, Salp Swarm Optimizer, corona virus herd immunity optimizer, lemurs optimizer, Lemurs optimizer, Dwarf-mongoose optimization, Salp swarm optimizer etc.[7] PSO has garnered ideas from swarm attribute of bird flocking or fish schooling. In the present work, techniques are elucidated such as Grey-Wolf optimization, AntLion optimization and Bacterial Colony (BCO) optimization.

In VANET, practically nodes are suffering from limited energy due to low battery life and random distribution. Thus, routing optimization is one of the most important key factors to decide the proper communication between nodes and finally sink hub through CH and also to minimize the energy consumption due to hopping and end-end delay. Routing Management defines proper path selection and timely transmission planning for affirming smooth and accurate data communication between nodes. Routing Management algorithm (RMO) ensures trust-worthy, intelligent and low data loss network system. Also, the RMO lowers the energy consumption, increases battery life and lengthen the overall lifespan of the network.[8]

This present work inspects the effectiveness of clustering algorithms in reducing power consumption within VANET. To achieve this power/energy management, three types of SI algorithms are thoroughly investigated in this manuscript. In the first part of the manuscript is the implementation of Grey-wolf algorithm (GWO) in order to search for optimization in power as well as efficient routing. GWO is distinguished by easy programming, simple working principle, void of parameters, devoid of derivation, user-friendliness, adaptability, flexibility, backbone of parallel distributed computing and robustness. It has the avenue of wolf position update, adaptive probability of mutation policy for improved hunting process, fitness function inspired migration operation. In this present work this GWO is applied to firstly identify the CH and then establishes the optimized network connections between CH and other members of the group followed by evaluation of minimum energy. Despite of this brighter side of GWO, slow convergence and stick to local optima, are the key disadvantages of this algorithm. To overcome this bottleneck of this algorithm, another nature inspired evolutionary algorithm is applied.

In the second phase of the manuscript, Ant-Lion optimization (ALO) is practiced to achieve the energy management as well as routing. The key advantages of Ant-Lion Optimizer are the fast convergence, strong balance between exploration and exploitation and novel Elitism to find out the best solution quickly. Also, the algorithm has the high chance to attain global search and avoidance of local optima.

For better understanding of clustering and routing management in order to attain minimum energy consumption by the nodes, another swarm intelligence technique is utilized. The last part of the manuscript emphasized on Bacterial Colony Optimization (BCO). The advantages of BCO are avoidance of premature convergence and widened global search due to bacterial chemotaxis and reproduction. This optimization technique also exploits local search efficiently. Finally, a comparative study was carried out for affirming optimized evolutionary algorithm.

2. Literature Review

Efficient routing is essential to provide safe and green data communication. This routing can be done through forming suitable cluster and appointment of a CH. The cluster formation, CH selection and nodal energy management can effectively perform by GWO. Numerous bits of evidence have been discovered supporting the effectiveness of GWO techniques. Ghaffari et.al. had documented GWO based clustering mechanism in routing the VANET's nodes. Their examination report revealed how the hierarchical cluster head appointment increases the overall throughput of the network. The overall performance of the algorithm was measured with the aid of different metrics such as packet delivery rate, end-to-end delay and outcome. The optimization protocol outperformed by 10%-25% in comparison to Particle Swarm Optimization, AODV-CD and weight-based clustering.[10] GWO is also capable to increase the life span of the Adhoc network due to dynamically changing the CH to reform optimal cluster. There is a continuous update in fitness value to select the CH. Such a phenomenon was observed by Zhao et.al., who reported the increment in the lifespan of Wireless Sensor Network(WSN) by 55.7%,46.3%, 31.9% and 27.0% respectively in comparison with non-meta heuristic protocols, including Stable Election Protocol abbreviated as SEP, modified SEP (M-SEP), distributed energy-efficient clustering algorithm (DEEC) in conjugation with fitness value based improved GWO (FIGWO) strategies.[11]The lifecycle of WSN at internet of Things (IoT) based smart systems is ended up due to node mobility induced multi-hop arrangement especially for the nodes near to sink. Multi-objective GWO proved itself as efficient routing protocol that can enhance lifetime of the network by 71%, 67%, 55%, and 38% compared to WRP (weighted rendezvous planning), EAPC (energy aware path construction), Dynamic Clustering Ant Colony Optimization (ACO) along with multi-objective Particle Swarm Optimization (MOPSO).[12] Reddy et.al. had highlighted the network lifetime enhancement, energy efficiency, throughput, network stability by Energy efficient GWO.[13] Adhoc on Demand Distance Vector (AODV) protocol when conjugated with GWO optimization technique, facilitates energy efficient, low hopping, reduced end-to-end delay and high throughput VANET or MANET system by optimizing fitness function.[14].This GWO is more efficient in providing energy efficient routing and load balancing as compared to Multi-objective Particle Swarm Optimization (MOPSO) and Comprehensive Learning Particle Swarm Optimization (CLPSO) after providing 10% of the total nodes as CH whereas the total CH count. The performance metrics were grid size, transmission range and number of nodes.[15] Enhanced safety is wholeheartedly urged for reliable communication and this safety can be achieved none other than by "Routing". Proper routing prevents data loss and on-time arrival of data packet to destination. Hybridized GWO technique such as Bat Hybridized GWO method (BHGWOM) can provide the best route between sender and receiver and also provides the notification of possible shortest route despite of different challenges including mobile topology, congestion, and energy consumption. The proposed model makes the composite effect of exploration ability of Bat algorithm and exploitation quality of GWO model. The hybrid model provides the quick convergence and accuracy in solution. The benchmarking outperformance of the model was obtained in terms of various optimization parameters such as congestion, delay and energy consumption in comparison with Ant Colony Optimization, Cuckoo Search Algorithm, Genetic Algorithm and GWO.[16] Another report has highlighted hybridized GWO model for energy minimization as well as security in data communication. The nodal energy optimization has been realized by skillful cluster formation facilitated by GWO technique whereas competent routing has been implemented by modified Sea Lion Optimization (SLO). Elliptic Curve Cryptography (ECC) has been incorporated to establish the security of the optimization model. The implementation of this composite model has improved the energy consumption by 12%, packet delivery ratio by 0.008 proportion, end-to end delay by 0.15, network throughput by 0.11 along with network life span by 15% with respect to other computational intelligence method.[17] Digra et.al. modified the GWO technique with the help of artificial bee colony, to prevent premature convergence as well as energy efficiency, network life span, speed of searching the preferable zone, number of active nodes, throughput but their investigation did not attempt the routing optimization.[18] The Elitism and global search ability of Antlion optimization drive the researcher to find out the quickest and best shortest path for data transmission. The augmented searching is achieved by the composite optimization technique formed by hybridization of AntLion Optimization and PSO models. The composite model was developed by Shwetha et. al. and they had demonstrated the best localization of sensor nodes for a WSN, achieved within 156 s which is comparatively lower than the other techniques. In this composite model, AntLion optimization minimized error in finding the location of WSN nodes whereas the PSO model provides the location accuracy with the aid of velocity and position update method.[19]The efficient CH selection in WSN is important for battery energy management and in this regard, AntLion optimization along with time division multiple access(TDMA) has been reported by Kavidha et.al.[20] AntLiON optimization technique has proven itself as cost-effective approach for developing suitable cluster for Wireless Body Area Network.(WBAN). The number of clusters and transmission range is inverse in relation. Therefore, within smaller transmission range, the optimizer provides higher clusters due to availability of fewer nodes. It also provides minimal number of optimal clusters as the grid size increases thus reduced the power consumption by the clusters.[3] Regarding exploration of CH candidate and dynamic capability, Bacterial Colony Optimization (BCO) offers remarkable advantage due to its chemotaxis and reproduction phase. The optimization has proven itself as an emerging competitive method for green MANET/VANET/WSN system in terms of residual energy of nodes, nodal proximity, communication costs. The performance of BCO system can be best evaluated in terms of number of alive nodes that symbolizes network's longevity, successful data transmission rate (throughput), residual energy of the nodes etc. C. Bala Subramanian and R. Ramkumar evaluated the performance of BCO with respect to other competitive optimization techniques and observed outperformance of BCO to provide the optimized power and network's longevity.[21] Till date, BCO is not investigated at high extent instead of which, bacterial foraging optimization (BFO) is massively reported. The basic difference in BFO and BCO lies in orientation in bacterial life cycle. BFO encourages single bacterium struggle for food, reproduction, swarming, elimination and disposal etc. whereas BCO offers a cluster of bacteria for searching for food and inter communication (swarming), reproduction, elimination and disposal. Thus, the collective behaviours of bacteria instigate the network system more exploitable and able for global search. To discern the research lacuna that necessitates the present endeavour, an assortment of previous scholarly works, along with the challenges they faced, has been carefully compiled in Table S1.

3. Results And Discussion

Comparative Study on total power against number of clusters and users, energy efficiency against number of clusters and users and clusters variation against transmission range before entering into the comparative analysis, the motivation, algorithms and the simulation parameters along with detailed methodology are described in Supplementary information (SI). Fig. S8-S13 depict individual total power variation against both the number of clusters as well as users, energy efficiency swing against the number of cluster and user and finally transmission range interrelation with number of clusters. All algorithms demonstrate a consistent increase in total power when the number of clusters increases, which is predicted as a result of increased communication overhead with denser cluster configurations. ALO consistently records the highest total power consumption across all cluster counts, achieving 160 units at 10 clusters, which suggests a relatively lower energy efficiency. ALO exhibits highest power usage (190 units for 10 users) whereas GWO offers moderate consumption (150 units) but astoundingly, BCO reveals lowest power consumption (110 units for 10 users) BCO proves itself as outperformer in minimization of total power consumption (Fig. S8,S10 and S12) In the context of energy efficiency, an opposite trend is observed across all cluster sizes, BCO attains the highest energy efficiency (20 to 150 units for clusters increment from 0 to 10) due to chemotactic behaviour leading to path selection and energy allocation. GWO performs intermediate and ALO becomes lowest energy efficient. For 10 users, BCO achieves extraordinary efficiency level of 200 units as compared to GWO (150 units) and ALO (140 units) (Fig. S9 A-B, S11A-B, S13A-B). For

GWO, there is a significant reduction in the number of clusters, decreasing from 200 to 20. This consistent decline suggests that as communication ranges increase, the necessity for dense clustering diminishes, allowing nodes to communicate directly over greater distances without the need for intermediary cluster heads or localized subgroups (Fig. S9C). ALO demonstrates superior intermediate energy performance and enhanced energy-to-coverage characteristics (Fig. S11C). BCO's exceptional transmission range illustrates its capacity to create efficient cluster formations that enhance overall network coverage, minimize communication gaps, and sustain strong multi-hop routing paths. This capability is particularly advantageous in scenarios where nodes are distributed sparsely or where long-range communication is necessary (Fig. S13C).

Comparative Study of GWO, ALO and BCO Optimization in Power Distribution with respect to cluster

Power distributions vs number of clusters

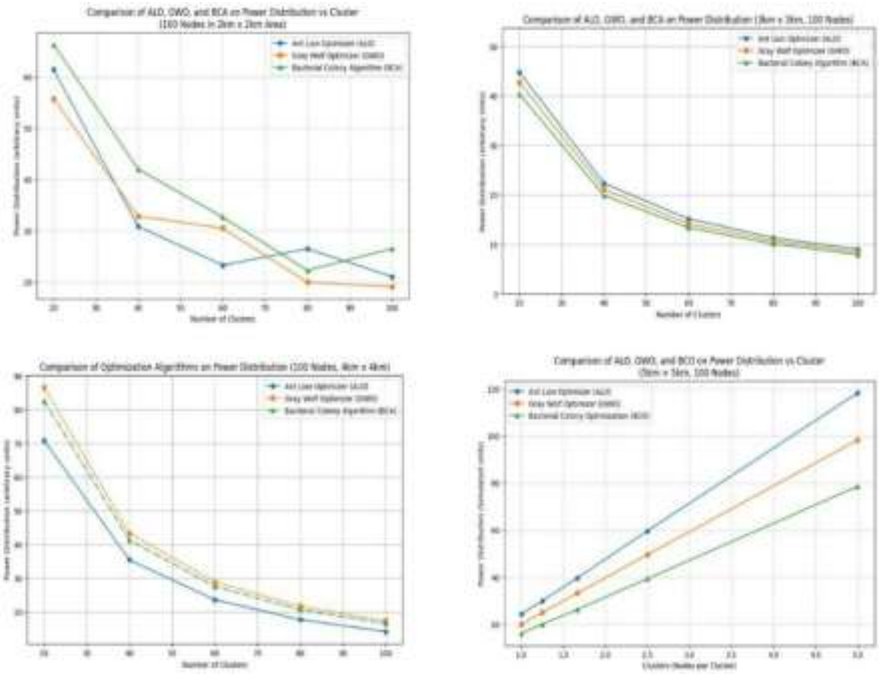

Figure 1. Power Distribution Variation Portfolio Against Number of Clusters for ALO, GWO, and BCO in NEMO Adhoc Network With 100 Nodes for Geographical Region Having (A) 2 km × 2 km, (B) 3 km × 3 km, (C) 4 km × 4 km, and (D) 5 km × 5 km Area

The power distribution profile as a function of cluster quantity for GWO, ALO and BCO when 100 nodes are present in a VANET (Fig. 1). The distribution profile is collected in various network deployment areas of size ranging from 2Km×2Km to 5Km×5Km accompanied with 100 vehicles. This distribution profile is signified metric in VANET as this metric unswervingly impacts three distinct parameters including network lifetime, energy consumption, and load balancing efficacy. For 2 km × 2 km, the power distribution profile follows decreasing fashion for all three optimization techniques. due to larger nodal communication distance and increased burden on CHs. In this particular case, ALO exhibited lower power distribution as compared to BCO and GWO beyond 40 clusters whereas BCO demonstrated less energy efficient framework for lower cluster numbers. This portfolio reflects energy efficient behaviour of ALO through adaptive search and exploitation mechanism. GWO exhibited moderate energy efficiency with higher power distribution for higher clusters. Now as we move on to investigate the power distribution profile for larger deployment areas such as 3 km×3 km, an even monotonic decrement in power distribution is observed for all three optimization techniques. This indicates improved energy efficiency with increasing cluster communication. ALO exhibited lost power distribution whereas BCO offers highest power consumption and GWO exhibited moderate performance. When the deployment area is increased to 4km×4km, the decrement in power values is much faster than the previous cases, as the cluster counts increases. This nature highlights the node dispersion in larger areas to improve inter cluster communication. This particular case also supports outperformance of ALO as compared to GWO and BCO. From the above analysis it is clear to us that for large-area communication, ALO will be wise choice to establish green power strategy. The decreasing trend of power distribution is juxtaposed for the widest deployment area (5 km ×5 km). Delicate observation reveals that more power is supplied to nodes to maintain intra-cluster communication for larger number of nodes per cluster. The gradual slope of ALO indicates efficient load balancing and CH selection. On the contrary BCO demonstrates local search priority and sub-optimal CH positioning. ALO proves to be most effect strategy for power optimization in large area where clusters are energy constrained. The performance of ALO also indicates its contribution in establishing most scalable VANET with prolonged lifetime, sustainable and green communication system.

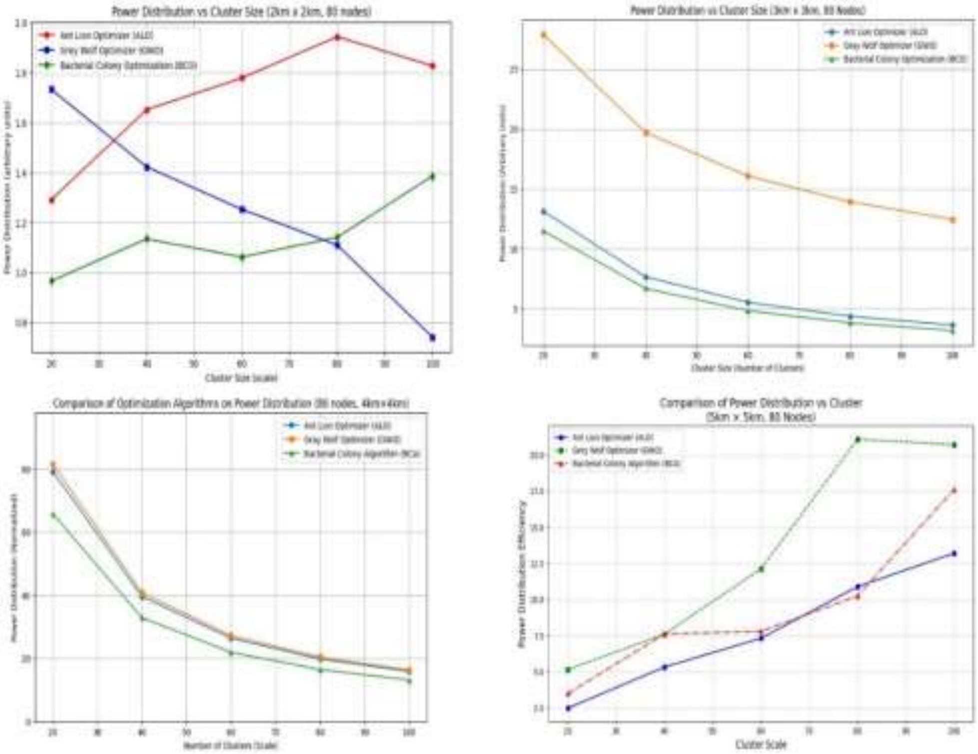

Figure 2. Power Distribution Variation Portfolio Against Number of Clusters for ALO, GWO, and BCO in NEMO Adhoc Network With 80 Nodes for Geographical Region Having (A) 2 km × 2 km, (B) 3 km × 3 km, (C) 4 km × 4 km, and (D) 5 km × 5 km Area.

In the figure 2, for smallest deployment area (2 km ×2 km), except GWO, both ALO and BCO exhibited non-monotonic behaviour towards power distribution over number of cluster selection. When the cluster size is increased, the intra-cluster communication overhead also increases and thereby increases the aggregation of intra-cluster communication. On the other side, if the number of clusters increases, there is a challenge to maintain load balancing and CH. In both cases, the power consumption increases to maintain communications between nodes. ALO offered higher power consumption when the cluster size was increasing from 20 to 40 indicating intra-cluster communication overheads. After that, the power consumption decreases at higher cluster sizes (80-100) due to reduced inter-cluster communication. GWO exhibited substantial decrement in power consumption as the cluster size is increased reflecting reduced intra-cluster communication distances as well as reduced burden on CH. BCO power consumption profile for small deployment area indicates inefficient load balancing and scalability. For slightly larger deployment area, a steady decrement in power consumption was observed for all three optimization techniques reflecting effective load balancing capability in higher cluster, reduced intra-cluster communication distance, reduced inter-cluster communication, effective communication with CH. In this context, ALO demonstrates lowest power consumption than all three algorithms particularly for higher cluster size. This reflects balancing transmission distances and communication aggregation. BCO demonstrated intermediate power consumption profile, specifically for higher cluster size, the power consumption is higher but for smaller and medium cluster size, it becomes moderate. GWO performs highest power distribution profile epitomizing less optimal CH placement. Similar observation was availed in large network (4 km ×4km) with more improved power consumption profile for GWO algorithm. For very large network (5 km ×5km), a contrast trend was observed for all three algorithms. Power distribution efficiency was increased for larger cluster size due to reduced CH and long-distance transmission. GWO devastatingly offered highest power distribution as the cluster size is increased. ALO in this case also, offers gradual increment in power distribution as the cluster size is increased. BCO provides increased power distribution but with less consistency. Thus, ALO offers stable and green communication framework.

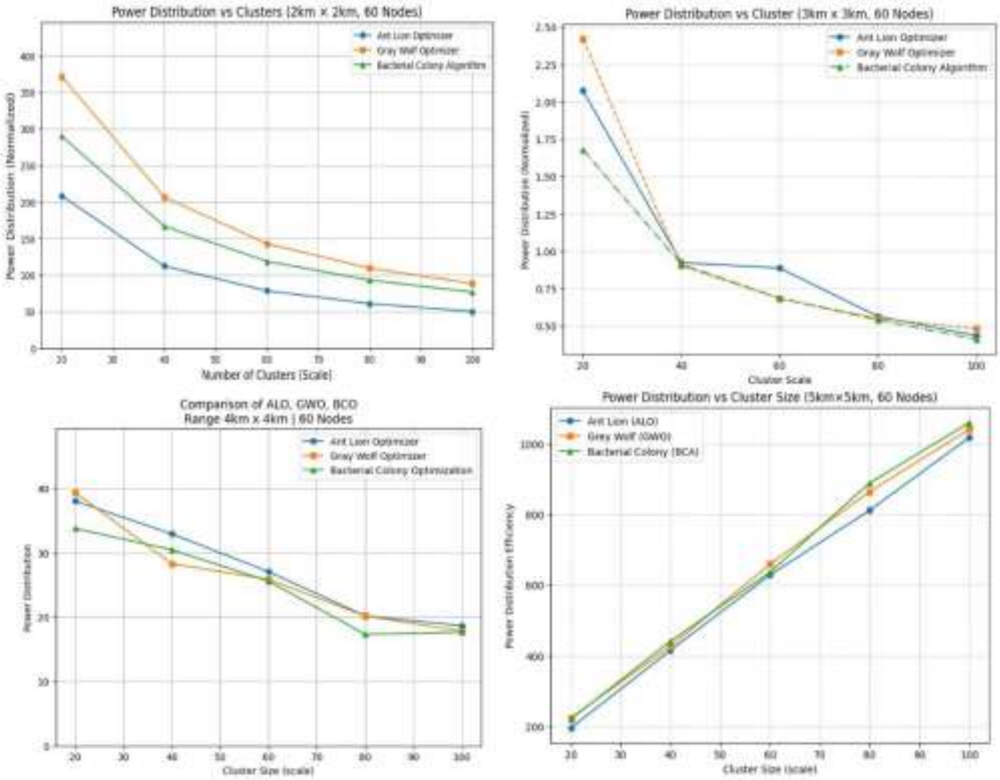

Fig. 3. Power Distribution Variation Portfolio Against Number of Clusters for ALO, GWO, and BCO in NEMO Adhoc Network With 60 Nodes for Geographical Region Having (A) 2 km × 2 km, (B) 3 km × 3 km, (C) 4 km × 4 km, and (D) 5 km × 5 km Area.

When the number of vehicles in a VANET framework becomes 60 and the VANET is expanding from smaller geographical area (2 km ×2 km) to larger area (5 km ×5km) the power distribution is varied with respect to cluster size according to Fig. 3.

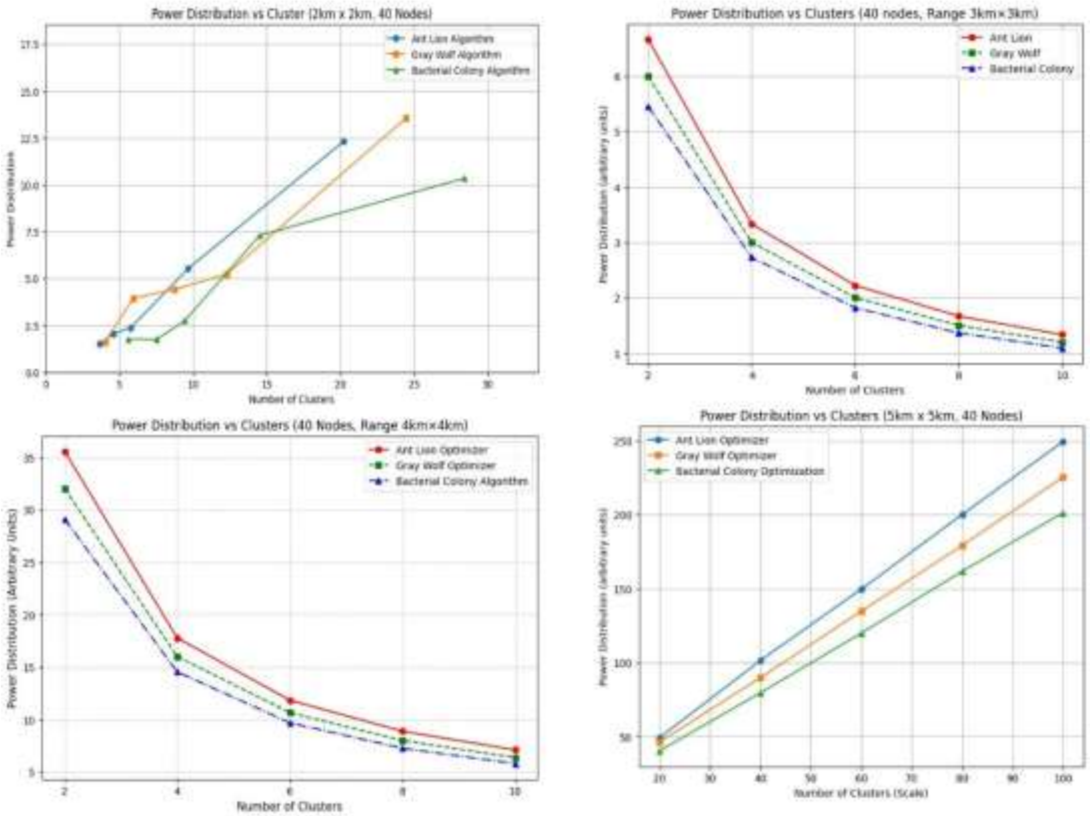

Figure 4. Power Distribution Variation Portfolio Against Number of Clusters for ALO, GWO, and BCO in NEMO Adhoc Network With 40 Nodes for Geographical Region Having (A) 2 km × 2 km, (B) 3 km × 3 km, (C) 4 km × 4 km, and (D) 5 km × 5 km Area.

Interesting point is that, the application of three different nature inspired algorithms promotes different dynamic nature of power distribution (Fig. 4). All the three algorithms exhibited decreasing attitude of power distribution for 2 km ×2 km area, when the cluster size is increased from 20 to 100. For low dense area, GWO provides highest power efficiency indicating poor control in energy minimisation, ALO provides lowest power distribution whereas BCO offers moderate power distribution among the clusters. Now when we are moving to highly dense area (larger number of clusters), all the three algorithms provide strong decrement in power distribution that is a positive indication of green communication strategy. In this context, ALO outperforms than BCO and GWO signifying adaptive random walk and exploitation ability to achieve minimal energy consumption. For 3 km ×3 km area, GWO and ALO exhibited higher power consumption in low dense area as compared to BCO but when the cluster size is increased to 40, all the three algorithms converge equally. The chemotaxis-induced local search strategy of BCO, aids to uphold stability at lo dense region. Interestingly for larger geographical areas, BCO outperforms than ALO due to bacterial foraging phenomenon that adapts to long distance communication cost while ALO’s random walk becomes more expensive. GWO performs moderately due to a balancing action between exploration and exploitation. A significant contrast is observed when the number of vehicles decreased to 40 in VANET (Fig 4). In this scenario, for smaller geographical area, all the three algorithms provide increased power consumption as the area is changing from low to high density. BCO outperforms than ALO and GWO due to chemotaxis phenomenon of BCO, overruling the random walk directed exploration ability of ALO. As the geographical area is expanding (3 km ×3 km) to (4 km ×4 km),the trend of power distribution over the cluster size is decreasing in nature and astonishingly, BCO outperforms than ALO (contradicted from higher nodes VANET configuration) because as the VANET area is increasing but with smaller nodes (here 40), the inter-cluster distance is increasing, to communicate with all the nodes present in a cluster by CH is seeking higher energy, this case is more prominent in smaller cluster size where the number of nodes are few. ALO incessant exploration ability is searching for elite ant-lion or best solution (minimal energy). This characteristic is mismatched with present requirement whereas BCO adaptive local search quickly reaches to local optima thus enabling energy efficiency. For higher cluster size, the inter cluster size is decreasing, thus ALO’s exploration ability is working properly thereby reduced the power consumption but BCO’s performance is still better than ALO as BCO’s foraging ability effectively balances the cluster size and transmission distance. For largest deployment area, power distribution increases linearly with cluster size for all three algorithms. For higher cluster size, the intra-cluster distance is increased so to reach minimal energy situation is difficult for ALO because of its continuous exploration attribute. In this BCO outpaces due to its distributed decision-making policy. For 20 nodes VANET, ALO outperforms than BCO and GWO for smallest geographical area while a monotonic increasing trend in power distribution over the cluster size is observed for all three algorithms (Fig. S14).

Comparative study of GWO, ALO, BCO for Number of cluster vs Transmission range

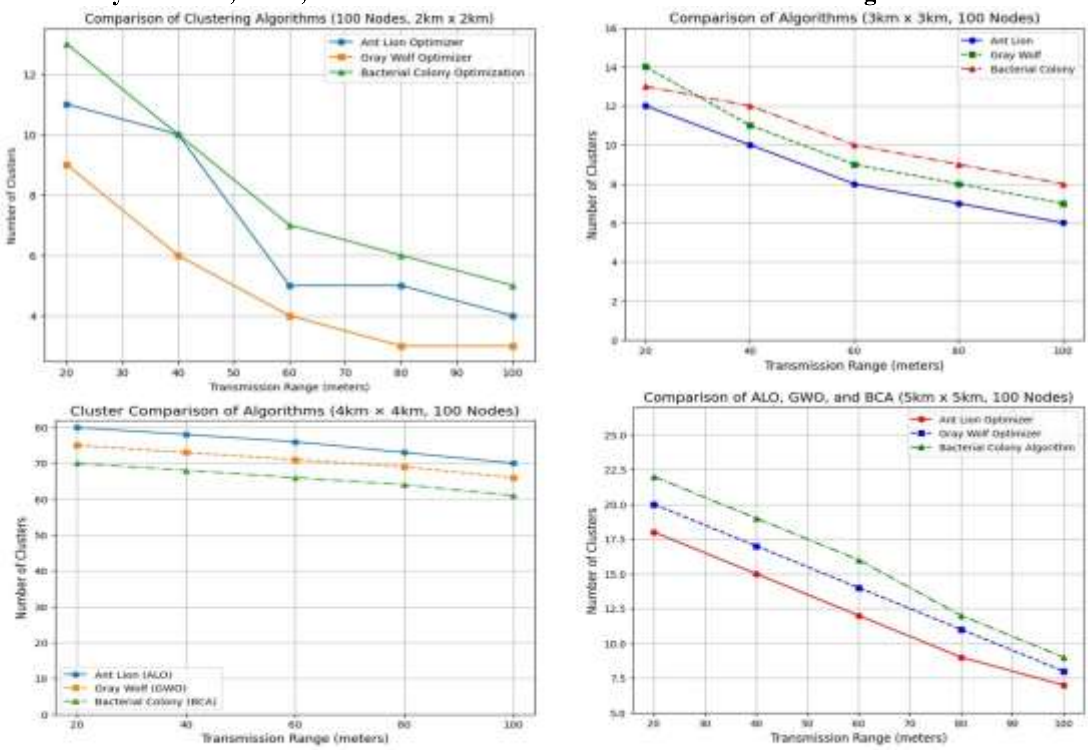

Figure 5. Number of Clusters Variation With Transmission Range (m) in NEMO Adhoc Network With 80 Nodes for Geographical Region Having (A) 2 km × 2 km, (B) 3 km × 3 km, (C) 4 km × 4 km, and (D) 5 km × 5 km Area When ALO, GWO, and BCO Are Applied.

For smallest deployment geographical area (2km ×2km) for a VANET with 100 nodes, an inverse connection is pragmatic between number of clusters and transmission range for the three nature--inspired meta—heuristic approaches (Fig. 5) BCO architected maximum number of clusters in smaller transmission range (20m), indicating favouring attribute of BCO for localized clustering. This kind of clustering can reduce the intra-cluster communication distances but the increase in transmission range helps in decline of clusters' quantity sharply for all the algorithms. Delicate observation reveals that GWO facilitates faster decline in cluster amount when transmission range is increased, especially when the distance is in between 80-100 m, the cluster quantity drastically fell (<4), this phenomenon pointed out the quick merging of clusters and achievement of global optima. ALO is characterized by intermediate cluster merging ability across the entire transmission range while BCO offers resistance in cluster merging throughout the transmission range, especially in higher ranges, it is very rigid in prohibiting global connection. (Fig. 5A) When we increase the size of the geographical area, say (3km ×3km), similar decreasing trend in cluster number is observed but the graph for all three algorithm experiences higher altitude (Fig. 5B). This higher- intense graphs reflect increased node dispersion to make the inter-cluster communication faster. For (4km ×4km), similar trend but with higher altitude is observed reflecting dense clustering for the sake of efficient interconnectivity across larger network. (Fig. 5C) For 5km ×5km area, linear decreasing pattern is observed but with lower cluster count. From these observations, it can be explained that ALO priorities lower cluster count particularly for higher transmission range for a dense VANET system that reflects long range connectivity in larger region (Fig. 5D).

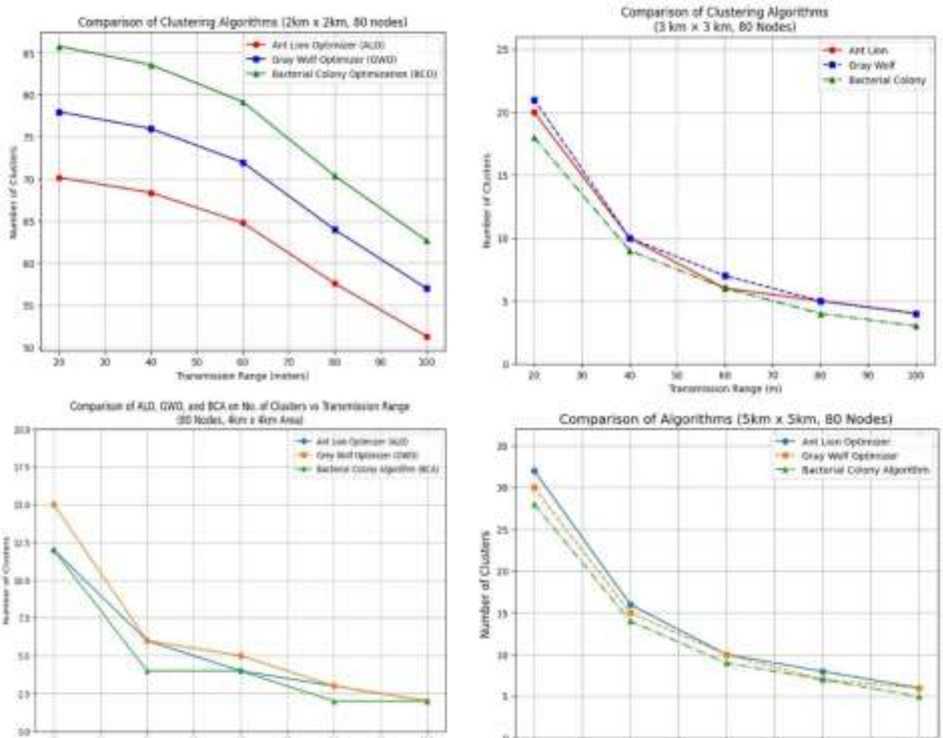

Figure 6. Number of clusters variation with transmission range(m) in NEMO Adhoc network with 80 nodes for geographical region having (A) 2 km × 2km (B) 3km × 3km (C) 4km × 4km and (D) 5km × 5km area when ALO, GWO and BCO are applied

BCO in this case, exhibited higher scalability due to highest cluster counts across all transmission ranges, GWO has moderate trend. For VANET framework with 80 nodes (Fig. 6), sincere decreasing pattern is observed for all kinds of geographic area when the three algorithms are implemented for efficient clustering. Acute inspection unveils that for larger area, BCO offers lower cluster count across transmission ranges where ALO offers higher cluster count across all transmission ranges reflecting scalability. For 60 nodes VANET, ALO and BCO showed higher cluster count than GWO (Fig. 7). In lowest and moderate deployment areas, ALO and GWO are preferred due to exploratory nature of GWO and province of stability over the granularity as mediated by ALO. The baseline i.e no optimization case, generates the highest cluster count (≈58–60) and after the application of these three algorithms, the number of clusters is reduced drastically. The acute comparative analysis unveils that among these three algorithms, BCO provides lowest cluster count with GWO moderate and ALO generates highest cluster framework to cover the entire transmission distances.

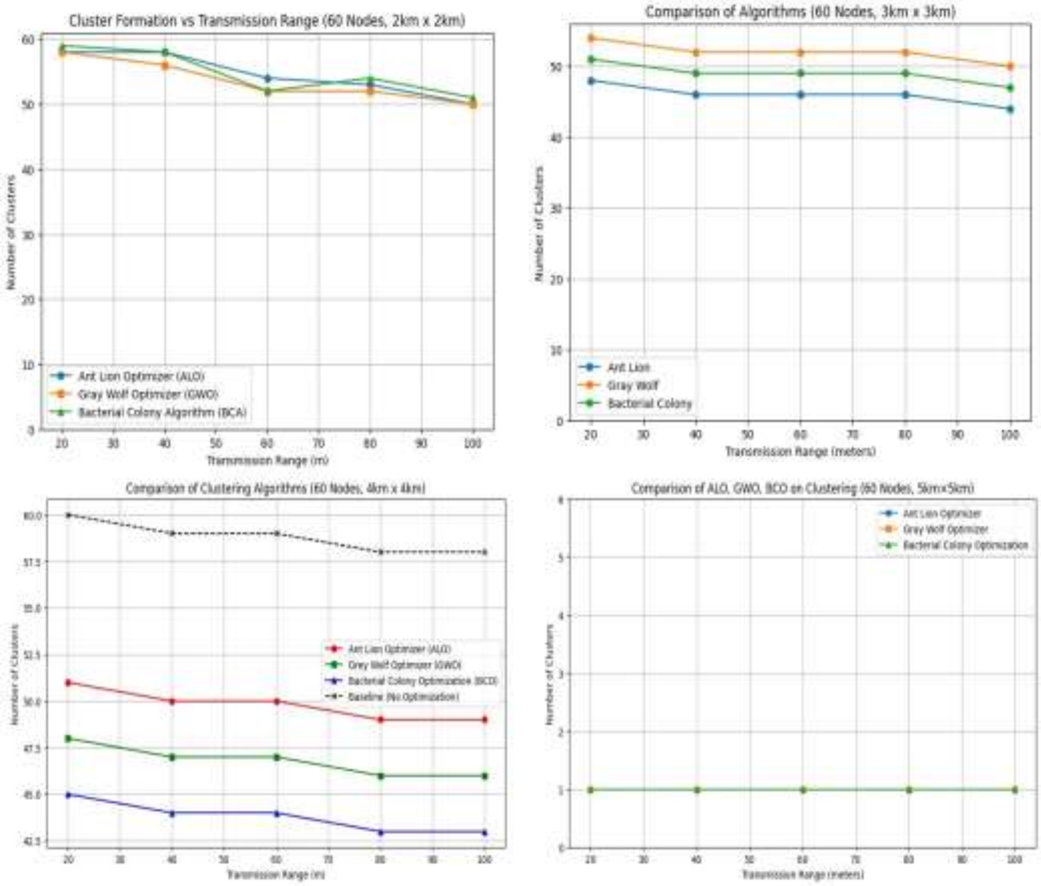

Figure 7. Number of Clusters Variation With Transmission Range (m) in NEMO Adhoc Network With 60 Nodes for Geographical Region Having (A) 2 km × 2 km, (B) 3 km × 3 km, (C) 4 km × 4 km, and (D) 5 km × 5 km Area When ALO, GWO, and BCO Are Applied.

On the contrary, the largest geographical area has witnessed only one cluster-based communication throughout the entire transmission range which reflects cluster-robustness and consistent convergence (Fig. 7(A)-(D)).

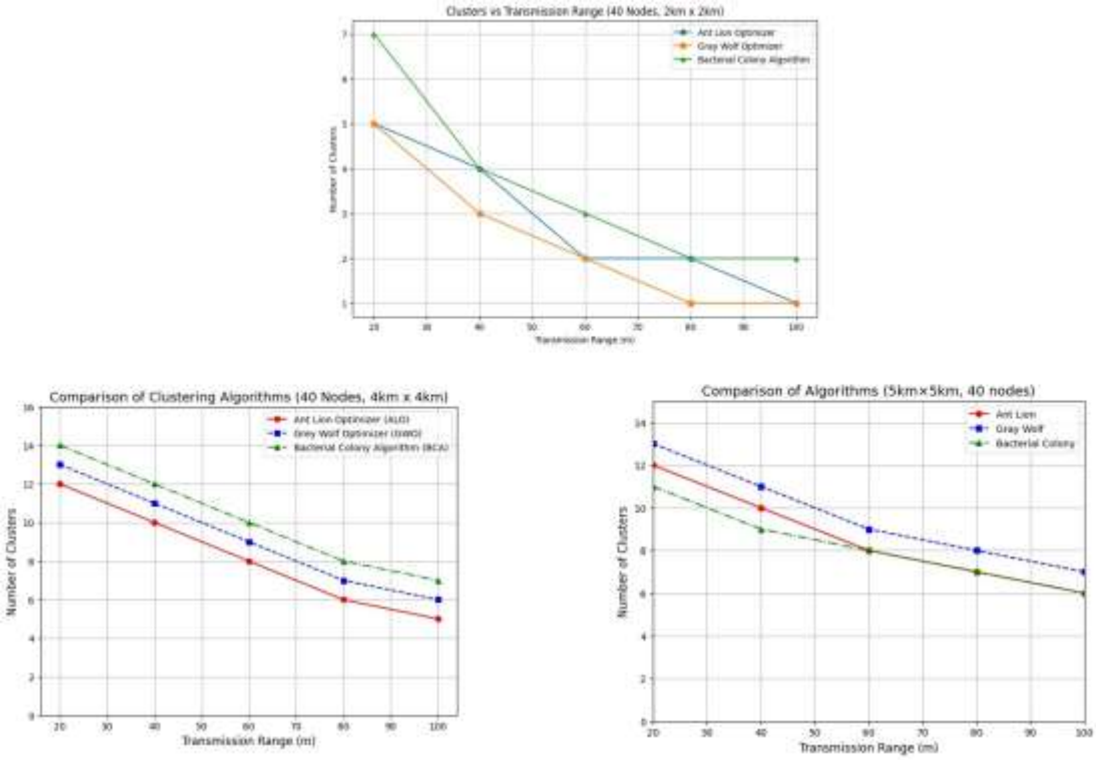

Figure 8. Number of Clusters Variation With Transmission Range (m) in NEMO Adhoc Network With 40 Nodes for Geographical Region Having (A) 2 km × 2 km, (B) 3 km × 3 km, (C) 4 km × 4 km, and (D) 5 km × 5 km Area When ALO, GWO, and BCO Are Applied.

As we think about the VANET with 40 nodes (vehicles), a decreasing pattern of cluster quantity across all transmission ranges are observed in varied network fields with these three algorithms (Fig. 8(A)-D)). When the network size is 2km ×2km, quick convergence is observed for ALO and GWO whereas BCO slowly converges (Fig. 8A). This competitiveness reflects the higher exploitation attribute of GWO particularly for smaller geographical area. As the network field size is increasing, all three algorithms start forming the larger cluster (12-14) and as the transmission range is increasing, the cluster quantity linearly decreases up to 80m, after that the trend is slowed down till 100m. ALO quickly attains convergence as compared to BCO while intermediate performance is maintained by GWO. For largest spatial scale (5km ×5km), monotonic decrease in cluster amount was visible for all three nature-inspire optimization techniques but ALO an BCO converges better than GWO reflecting higher exploitation ability of ALO and BCO but higher cluster diversity of GWO(Fig.20(D)) In case of smaller deployment area (2km ×2km) with low node density (20 nodes) (Fig.21A), the initial cluster count is low and all the three algorithms offer sharp decline in cluster amount (final cluster count=1 at transmission distance=100m) reflecting direct contact with distant neighbours without creating larger cluster. Among these three algorithms, BCO quickly converges due to conservative cluster creation. GWO offers relatively slower convergence due to distributive clustering. For medium deployment area (3km ×3km) (Fig. 21B), the clustering pattern experiences monotonic increment over the transmission ranges indicating diverse clustering. Among, these three clustering techniques, GWO offers rapid increase in cluster quantity reflecting creation of additional cluster heads due to exploration-based hierarchy. In high spatial scale with small node density (4km ×4km) (Fig. 21C), all the three algorithms started with large amount of cluster especially from lowest transmission range (20m) to establish a effective communication network. In this situation, ALO exhibited fewest cluster reflecting elitism-based optimization whereas GWO demonstrated intermediate trend mirroring exploration-exploitation based convergence through hierarchical hunting process. Unfortunately, BCO has proven itself as slow performer in cluster convergence. In case of large deployment area with low node density (Fig. 21D), the cluster count becomes relatively stable for all three algorithms across the transmission ranges. ALO generates minimum clusters but a constant quantity from 40m–100m indicating merging of different clusters to make the communication among nodes throughout this deployment area. BCO also showed similar trend but with moderate level, reflecting balanced exploration-exploitation strategies. On the contrary, GWO offers highest cluster count reflecting spatial diverse clustering attribute.

4. Conclusion

This study conducted a thorough and systematic comparative analysis of three advanced meta-heuristic optimization methods—Grey Wolf Optimization (GWO), Ant Lion Optimization (ALO), and Bacterial Colony Optimization (BCO)—aimed at energy-efficient clustering and routing within Vehicular Ad hoc Networks. Considering the strict energy limitations, frequent changes in topology, and the scalability demands associated with VANETs, intelligent cluster-based routing was recognized as an effective approach to improve network sustainability and communication efficiency. Through comprehensive modelling and simulation, it was shown that all three optimization methods can enhance cluster-head selection and decrease energy dissipation when compared to traditional routing techniques. GWO demonstrated dependable hierarchical control and organized convergence but was prone to premature convergence during later iterations. ALO enhanced the balance between exploration and exploitation through elitism and stochastic random walks, leading to quicker convergence and better routing stability. Nevertheless, the most significant performance improvements were observed with Bacterial Colony Optimization. By utilizing collective bacterial behaviour, chemotaxis-driven communication, and reproduction-based selection, BCO consistently achieved reduced power consumption, improved global search capabilities, and superior convergence characteristics. The comparative results distinctly demonstrate that BCO offers a more robust and energy-efficient clustering framework tailored for highly dynamic vehicular environments. The proposed approach not only enhances network longevity but also guarantees scalable and adaptive routing that is appropriate for practical VANET implementations. In summary, this research provides a thorough performance benchmark of swarm-intelligence-based optimizers for energy management in VANETs and positions BCO as a promising option for future green vehicular communication systems. Future research may expand this framework to include multi-objective optimization that addresses delay, security, and quality-of-service requirements within diverse vehicular mobility scenarios.

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