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https://doi.org/10.5109/6793654

出版情報：Evergreen. 10 (2), pp.998-1009, 2023-06. 九州大学グリーンテクノロジー研究教育センター
バージョン：

EVERGREEN Joint Journal of Novel Carbon Resource Sciences & Green Asia Strategy, Vol. 10, Issue 02, pp998-1009, June 2023

Ant Colony Optimization Based Routing Strategies for Internet of Things

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(Received March 6, 2023; Revised May 3, 2023; accepted June 1, 2023).

Abstract: In this paper, two meta-heuristic approaches have been optimized using SI (Swarm Intelligence) optimization technique. The method comprises computation of shortest path of both, static and dynamic IoT (Internet of Things) network using "widely used algorithms" among researchers, namely, 'Breadth first search' and 'Dijkstra algorithm.' Further, the determined route has been optimized using ant colony optimization. The issue of route selection to reach the destination, as well as parameters such as network energy, departed node count, residual energy of IoT nodes, and critical points of IoT nodes have been explored using proposed smart routing techniques. The two unique routing approaches have been simulated with rigorous iteration run, i=2000. The proposed methods, 'Ant colony optimization- Breadth first computation-Minkowski-Static' (ABMS) technique and 'Ant colony optimization-Breadth first computation-Minkowski-Dynamic' (ABMD) technique have been simulated. After comparing efficiency between both techniques, ABMS method outperforms the ABMD routing technique for IoT network. A significant energy savings has been reported, extending network lifetime of a static IoT network scenario. With the implementation of both techniques, the comparison between dynamic and static results closely.

Keywords: Routing, Swarm Intelligence, Ant colony optimization, ABMS (Ant colony optimization- Breadth first computation-Minkowski-Static), ABMD (Ant colony optimization-Breadth first computation-Minkowski-Dynamic), Internet of Things.

1. Introduction

The smart devices can actuate and communicate with other devices, bringing adaptability to the 'Internet of Things' concept. The Internet of Things (IoT), a new technology that allow for the creation of dynamic Plug & Play smart device applications[1)] .The proliferation of Internet-of-Things (IoT) devices is driving up demand for effective processing of low-latency stream data generated near the network's edge[2)] .The soft computing-based stream processing approaches that reflect the variety of computational and network resources available in the infrastructure can significantly improve data stream throughput and end-to-end latency[3)] .

Swarm Intelligence signifies the behavior of group of living organisms collectively. Here, investigation used to find the solution. Individual behavior guidelines and local information are used to improve communication. The interaction between the insects and their surroundings determines the overall system behavior. The PSO (Particle Swarm Optimization) has an advantage of fast convergence. A Population-based optimization method contains a group of individuals, moving in multi-dimensional space[4)] . Each particle possesses position and velocity at any instant of time. Each particle returns to its best surrounding path with global best location correspondingly[5)] .The updating in velocity and position continued until the best possible solution is determined[6)] . ACO (Ant Colony Optimization) aids in simulation of meta-heuristic systems. In this algorithm, some fundamentals are adopted in order to break free from local optima[7)] .The method starts with a null solution and then add parts to create a decent full solution. In local search heuristic, initializing with random solution and then modifying it as iterations go through to get a better solution. The primary aspect of ACO algorithm includes combining of priori information about structuring of prospective solution with posteriori change in the structure of previously obtained good solutions. By navigating through a search space, it represents all possible solutions and the simulation agents discover optimal solutions. The artificial ants, likewise real ants, keep track of their positions and the quality of solutions for preparing the next stage. The left-over simulated ants discover a better solution.

In this paper, two approaches have been proposed and evaluated their network efficiencies by comparing each other based on various outcome parameters. The first approach, ABMS (Ant colony optimization-Breadth first computation-Minkowski-Static). The implementation of ABMS routing approach, the network of IoT nodes kept stationary. The shortest path has been determined using breadth first computation and thereafter, ant colony optimization, optimizes the route. The second approach namely, ABMD (Ant colony optimization-Breadth first computation-Minkowski-Dynamic). In this approach, the IoT nodes in the network with mobility 9m/s. The 'Minkowski' is the distance type taken between any two IoT nodes of the network. Here, IoT nodes are not rechargeable gadgets. Once the IoT nodes get run out of battery, they die.

In comparison to other peripheral nodes in the network, nodes nearby the sink transfers more data through them. The IoT nodes send data to sink node in a multi-hop fashion during communication. Therefore, nodes being closer to the sink have a higher chance of running out of energy faster than nodes that are located farther away. Two most critical challenges to solve multi- hopping routing and data traffic concentration near the sink. The related IoT nodes are called 'hot nodes,' and the problem is known as the 'Hotspot Problem' or 'energy hole problem.' The concept of 'dropping hotspot' introduced and implemented to tackle the obstacle of resolving hotspot issues. Thus, propose work focuses on balancing energy consumption among IoT nodes. The hot nodes being dropped in the network at 50% drop rate.

This paper comprises of comparison between static and dynamic IoT network scenarios with an aim of reducing consumption of network energy and increase network lifetime for sustainable communication in IoT. The comparison among the two routing approaches results outperformance of ABMS routing over ABMD routing strategy.

1.1 Ant Colony Model:

Ant begins to move in all directions in search of food resources. Ants leave a chemical trail known as 'pheromone' when they return to the colony. As more ants come across the track, they choose a path that follows the trail at random. If they find a resource at the end of the route, leaving the trail behind while returning to the colony. Though, as time passes, the pheromone's potency diminishes. The 'evaporation of pheromone' mechanism prevents convergence at a local optimal. The path chosen by the leading ant has the highest chance of being followed by the other ants. Hence, the rate of evaporation of chemical released by ants enables other ants to locate new resource locations. Real ants prefer pursuing chemically concentrated pathways. In order to solve combinatorial optimization problems, artificial ants are also customized with these characteristics of actual ants. Many eminent scholars have provided insight into the complex social behavior of ants. Fig. 1, depicts the general principles and steps involved in ACO model.

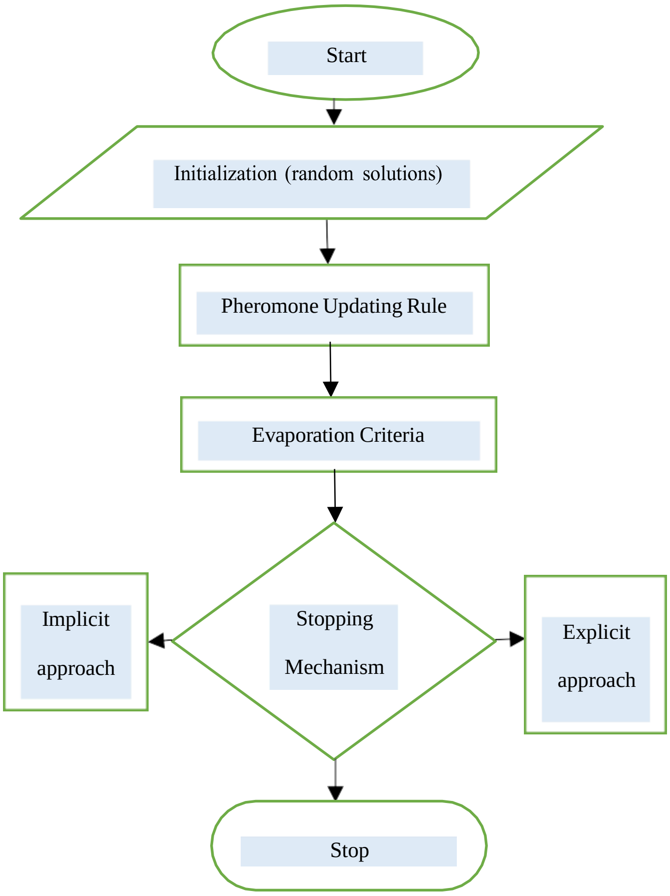


Fig. 1: Flowchart of Ant Colony System

The initialization as description of the problem and declaration of the number of ants. Initializing conditions include a pheromone trail, a constant concentration of chemical laid by ants, and evaporation rate. The path in the network corresponds to the feasible solution. The number of ants distributed among the network are randomly chosen nodes. The distribution of ants on different nodes will begin a network tour and build a path using the probabilistic decision criteria. According to Pheromone updating rule, each ant's pheromone updated at the end of the cycle. An ACO algorithm comprises of one cycle after each ant constructs its solution. Using ant transition rule, ants move through different paths until a solution to problem determined. The updating rule updates the pheromone concentration. Using the Evaporation criteria, the chemical trail strength evaporates before the pheromone is updated. The current partial path stored by every ant through antennae. As a result, ant traces their own route. Stopping mechanism could be a declaration on the number of iterations or CPU time. Those ants that have already travelled a path provide feedback to the system. Two ways can be used to study the generated solution. Implicit approach being a technique that could be followed for natural distributive problem. The approach exploits differential route length. When an ant traverses a shorter route, it deposits pheromone on it[8]. As a result, approaching ants search become skewed. Using explicit approach, the generated quality of solution determines the amount of updated pheromone.

When the number of ants greater than the number of search ants in the recruitment approach. These ants are called recruiting ants. The Two types of ants have been discussed. First one, 'Search Ant' searches for solution randomly in the surroundings[9] .Another class of ants are 'Transport Ant.' Their working begins after an acceptable solution[10].The route with highest probability followed for transporting food.

The pheromone mediated finds utility for indirect communication. It establishes a feedback loop. This enables left over ants to take decision regarding selected route. There are local and global pheromone trail models available to be implement during simulation[11] .Fig. 2, highlighted the updating model.

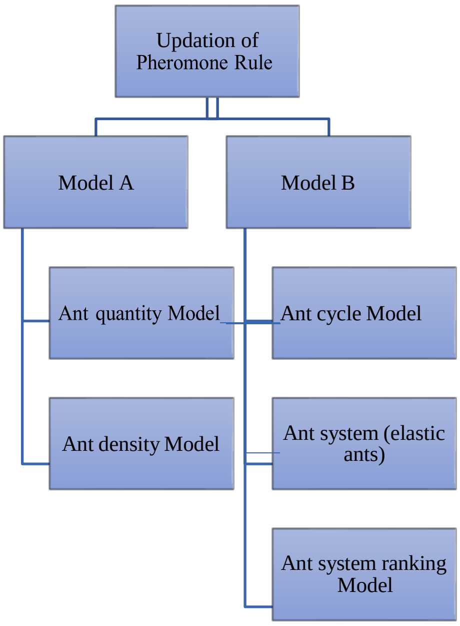


Fig.2: Updating Models Classification

MODEL-A: Local updating of pheromone trail. Ant updates the pheromone trail on the path locally. Ant density model, on the route i j, an ant travelling from node i to node j leaves a given density of chemical trace.

MODEL-B: Global updating of pheromone trail. The length of the tour is inversely proportional to the amount of pheromone trail deposited. In Ant cycle model, after the completion of each cycle by all ants, the trail is updated globally. The path may be retraced with deposited pheromone. The concentration of pheromone left by each ant act as the function of the path quality. The Ant system with elastic ants similar to the ant cycle model. An elastic ant, a designation given to cluster of ants, reinforces the best path calculated for the efficient routing. In Ant system ranking model, the global best path calculated and updated. Also, pheromone trail has been deposited by cluster of best ants of current iteration.

2. Literature Studies

The existing literature has indicated that the ACO has been implemented frequently to determine mobile sink trajectory. Hence, ant colony system-based approaches, namely, ABMS and ABMD have been proposed.

Kamal Kumar Gola et al.[12] reviewed the underwater Wireless Sensor Network (WSN) based on localization and routing. The study advances the understanding of WSN, which further provide a criterion to compare and develop more efficient performance- enhancing techniques. SK Narayana et al.[13] explored WSN routing reliability and data privacy. This study has proposed the term, 'PTEACO.' It has been analyzed using some metrics. An upgraded Dijkstra algorithm, round-trip time-based detection and proposed scheme has been compared with existing methods. Ali Seyfollahi et al.[14] discussed effectiveness and stability ofthe IoT network onrouting and data transmission operations. Due to the constrained energy resources of IoT devices, energy efficiency and proper load balancing between sensing devices present significant challenges. Ali Kooshari et al.[15]determined optimal path for sustained communication in WSN in context with low network energy consumption and a reduced amount of error rate. Tri-Hai et al.[16] focused on solving traffic congestion problem using ACO algorithm in IoT network. The proposed research shortens the travel time and subsequently fuel consumption has been decreased. Yuhui Shi et al.[17] investigated population diversity approach for avoidingpremature convergence in PSO and designing efficient algorithms. Xiaochun Wang et al.[18] investigated a cluster-based outlier detection strategy that may partially overcome the least spanning tree algorithm's efficiency affecting parameters. It has a broad range of applications in data mining. Anukriti Sharma et al.[19] studied into existing IoT routing technologies and investigated various routing algorithms. According to the findings, Flat routing outperformed communicated hierarchical routing for ad- hoc networks. Aman Ullah et al.[20] examined an effective distance-based centrality technique for identifying prominent nodes in a network. The characteristics like Degree nodes, k shell power, adjacent node potential, and link distance are all compromised for the given algorithm have also played a significant role in wireless communication. Sharad Sharma et al.[21] investigated TCO behavior and determined it to be the cheapest option to improve network performance in constantly changing network conditions. Wireless Mesh Networks have also played a significant role in wireless communication. Anukriti Sharma et al.[22] discussed concepts of IoT and the importance of sensors in the environment. Its significance in the future has been explained. A comparison resulted that Tabu search proved to be superior from existing routing techniques for calculating shortest distance in the network. Xiaochen Chou et al.[23] projected a constrained combinational metaheuristic tabu method with an incorporated Monte Carlo evaluator as a solution. In addition, adoption to the Orienteering routing problem using variants with potential clients was accomplished to boost revenue. Sharad Sharma et al.[24] investigated an efficient routing approach inspired by ant foraging behavior in order to improve network efficiency while maximizing network resource consumption. The proposed Ant Mesh Net method outperforms AODV algorithm for same Wireless Mesh Network.

According to research mentioned by Saima khan et al.[25] the algorithm of search diversity includes theproduction of a variety of solutions that will enableimprovements in ship operations. The authors simulated the Dijkstra algorithm to solve difficult problems andupdate the shortest-route from the origin node (city) to the destination node (other cities) in less time andexpense. The simulation capacity to seek the most cost-effective route in the lowest possible time (seconds)demonstrated by a test achieved 95 percent successrate[26] .The results of the experiments done by theresearchers, proved that the proposed strategy as goodway to schedule nodes for monitoring all targets withless energy. All the experimental data gathered to showthat the proposed strategy has validated the problem description and accomplished the project goal[27] . Patricia et al.[28] evaluated the traveling salesman issue,NP-hard problem commonly utilized in the literature totest combinatorial optimization. An extensive evaluation was conducted using three medium and large sizesinstances from the TSPLIB library, and revealed superlinear speedups over the sequential algorithm withscalability. Hessam Moeini et al.[29] developed semantic-based routing protocol to lower the memory needed forrouting with IoT services. The notion of telescopic visionwas also realized using an ontology-based coding scheme and an ontology of capabilities summarizingapproach. Sharad Sharma et al. [30] examined the routingprocess by adopting Grey Wolf Optimization with reduced energy consumption, delay time and bandwidthrequired correspondingly for the IoT network. Trond Hammervollet al.[31] explored the application of TPPS toovercome distribution hinderances faced by companies.

3. Methodology

The projected novel routing approaches based on BFS (Breadth first search) and ACO (Ant colony optimization) have been implemented in static and dynamic IoT network scenarios respectively. The proposed solutions have two stages for lowering network energy consumption. The shortest path is determined using breadth first search algorithm and then optimize the obtained path. The Clustering is a way to cut down network energy consumption. The cluster head moves to the next stage after receiving data and repeats the process until data reaches the sink via a multihop mechanism. The nodes located nearby sink reached a critical point due to overload of transmitting data. These overloaded nodes are referred to as 'Hotspots.' Distance of each node from the sink has been calculated. Hotspots are nodes that are within the maximum transmission range. The hot nodes are dropped, and the remaining nodes will function as forward nodes. So, dropping down of hotspot avoids network communication breakage. A 'Drop mode' as a novelty factor has been introduced in the routing techniques. The dropping rate being 50% during the routing. Considering IoT nodes with high fitness function value in the network so that uniform load can be distributed among the nodes. Thus, optimized routing starts in the hotspot area.

For the first round of ACO, random initialization of the solution is done. Ant P, Parent ants are initialized. Fitness function has been implemented corresponding to the given fitness function equation as mentioned below in the paper. With dropping down the ants, checking task of consumed energy by ants during communication has been accomplished. The load on individual node being checked and load balancing is performed. Now, fitness function matrix is generated. The fitness value of individual nodes depending upon dropped or un dropped generated correspondingly. In this study, optimization has been kept maximum. The mutation in every parent ant has been completed. Ant C, changes caused in parent ant according to ACO, termed as child ant. Now, fitness function of child ants being checked. A comparison has been placed between fitness function of child ant and parent ant. If the condition persists that fitness function value of child ant is greater than its parent ant respectively then exchange in position of parent ant with child ant performed. Again, maximum fitness value of other parent ants has been checked and compared with their child ant. This is the working of first round ant colony optimization and the process continues. Other parameters associated with genetic algorithm considered as residual energy of nodes, transmission distance, neighborhood nodes. The genetic algorithm applied and nodes for further transmission selected using defined crossover and mutation.

3.1 Flowchart of Proposed Routing Strategies:

The proposed algorithm approach has been outlined using Flowchart as depicted in Fig 3.

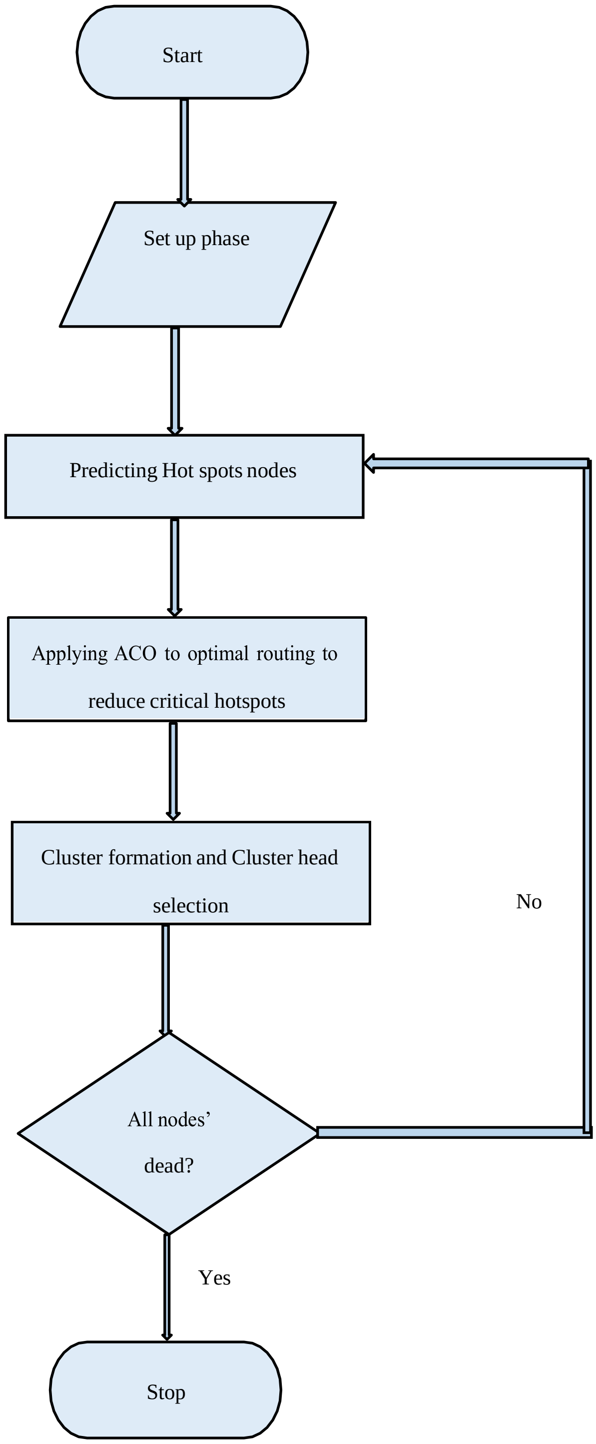


Fig. 3: Flowchart of Proposed Routing Strategies

4. System Model

In the system model, each model such as distance type inthe network, equations for proposed approach, energy model and fitness function present unique perspective to understand the platform for the routing technique.

4.1 Minkowski Distance:

The 'Minkowski Distance' has been considered as the distance type between IoT nodes for the network. It may be defined mathematically as shown below:

Suppose, given two nodes, $x = (p_1, p_2, ..., p_n)$ and $y = (q_1, q_2, ..., q_n)$

then the 'Minkowski Distance', *'d'* between *x* and *y* of order *p* is calculated as:

$$d = \sqrt[p]{|p_1 - q_1| + |p_2 - q_2| + ... + |p_n - q_n|} \quad (1)$$

4.2 Proposed Approach Based on ACO: Equation:

It becomes essential to predict the optimal path for the network in order to realize network optimization. At time t, each ant chooses the following path for upgrading the proposed ant colony optimization process, as stated by the probability formula:

$$T^r_{lm} = \begin{cases} \dfrac{[\pi_{mn}(t)]^{\omega}[\tau_{mn}(t)]^{\rho}[\chi_{mn}(t)]^{\upsilon}U_n}{\sum_{G \subset acceptable_r}[\pi_{ml}(t)]^{\omega}[\tau_{ml}(t)]^{\rho}[\chi_{ml}(t)]^{\upsilon}U_l} & n \subset acceptable_r \\ 0 & Otherwise \end{cases}$$

$$\text{Where, } \tau_{mn}(t) = \frac{1}{b_{mn}} \quad (2)$$

Where $\pi_{mn}(t)$ the pheromone concentration on *m, n* edges and τ_{mn} is the desirability. The heuristic information present on edge *(m, n)*. Also, two impact factors ρ, ω control the influence of heuristic information and pheromone concentration accordingly. According to the average mobility, speed of the nodes, $\chi_{mn}(t)$ the calculatedstability factor. Here, *v* a constant for inclining or declining the effect of the stability. The remaining energyof a device is U_n and number of ant r visit. The distance between *m* and *n* as b_{mn}. According to the following equation the amount of pheromone updated.

$$\pi_{mn}(t+1) = (1-\sigma)\tau_{mn}(t) + \Delta\tau_{mn}(t) \quad (3)$$

$$\Delta\pi_{mn}(t) = \sum_{i=1}^{t} \Delta\pi^{i}_{mn} \quad (4)$$

Where, σ evaporation coefficient of pheromone, $\Delta\pi_{mn}(t)$ is amount of pheromone deposited of edge *m, n* usually given by,

$$\Delta\pi^k_{mn} = \begin{cases} \dfrac{H}{M_k} & \text{if ant k use on edge (m,n)} \\ 0 & otherwise \end{cases} \quad (5)$$

Here, M_k the length of the k^{th} ant's visit. The constant *H* represents pheromone strength.

4.3 Energy Model:

The multi hopping model has been used to transfer data across distant locations. The energy consumed by sensing devices calculated from energy equations as shown below. The proposed method incorporates the radio framework where value k_0 equals 87.7m.

$$G_{trans}(\alpha, k) = \begin{cases} \alpha G_{elec} + \alpha\varepsilon_{fs} k^2 & if\, k < k_0 \\ \alpha G_{elec} + \alpha\varepsilon_{mp} k^4 & if\, k \geq k_0 \end{cases} \tag{6}$$

Where, α- bit is number of bits transmitted over a long-distance k. The path loss components are k^2, k^4. The transmitted power dissipated by G_{elec}. Its value being constant. The energy required by an amplifier represented as in free space using symbol ε_{fs}. With increase in distance, the transmission power increases up to k_0. Furthermore, while using the multi-hopping model, the amount of energy spent is given by amplifier constant ε_{mp}. It is antenna amplifier parameter. The threshold value for energy consumed by sensing device for short-range transmission represented with symbol k_0. If G_{compk} the total energy level of the sensing device and G_{transk} as transmission energy. Then, for instance, G_{resk} the left-over energy of a gadget can be calculated as follows:

$$G_{res_k} = G_{comp_k} - G_{trans_k} \tag{7}$$

4.4 Fitness Function:

In order to calculate the optimal solution, a fitness function has been used as an objective function for the proposed routing strategies. The nodes with the highest fitness value considered as the finest solution. The fitness value of the parent ant is compared to that of its progeny during the mutation in the ant colony system. If the fitness value of child is greater than the value of parent. Then, the child ant positioned solutions are swapped with previous solutions and updation occurs.

$$(Fitness\_Value)_{(K)} = \frac{\sum_{i=1}^{n} G_{res(i)}}{(No.\ of\ selected\ nodes)} \tag{8}$$

Where, n is the number of overloaded hot nodes detected for k_{th} communication iteration. The proposed approach tends to optimize maximum value of the fitness function.

5. Results and Discussion

The software MATLAB 2018b used for performing simulation over proposed optimized routing techniques, 'ABMS and ABMD' individually. A comparison has been done between these techniques to evaluate their network efficiencies. Table 1. outlines the initialization parameters and their corresponding values implemented during simulation of routing techniques. The size of network considered with cross- sectional100x100m^2. The position of sink node = range/2, number of sensors=100, number of ants (solutions)=10 with 15 ACO iterations. Assuming the initial energy provided thenetwork varies between (0.2 joule to 0.4 joule). Incorporating the fitness function value with g=40m with mobility speed m=0m/s for ABMS and m=9m/s for ABMD. The assumed parameters include the transmitted packet length of 4000 bits.

Table 1: Simulation Parameters

Parameters	Value
Network range	[100,100]m^2
IoT nodes in Number	100
Transmission range(g)	40 m
Packet length(l)	4000 bits
Initial Energy	0.2 J – 0.4 J
Distance Threshold (k_0)	87.7
Dropping Hot node rate	50%
Mobility	0m/s for ABMS, 9 m/sec for ABMD
Number of ants	10
Structure of arrangement of nodes in the network	Uniformly randomly deployment of IoT nodes

Fig. 4 depicts IoT network with stationary sensing nodes dispensed within network range of 100m x 100m. The shortest distance has been calculated using BFC (Breadth First Computation). The sensing elements have been deployed uniformly randomly between the grid lines. Only the unique sensors are placed inside the defined cross- sectional network coverage with inner boundary width, w=4m.

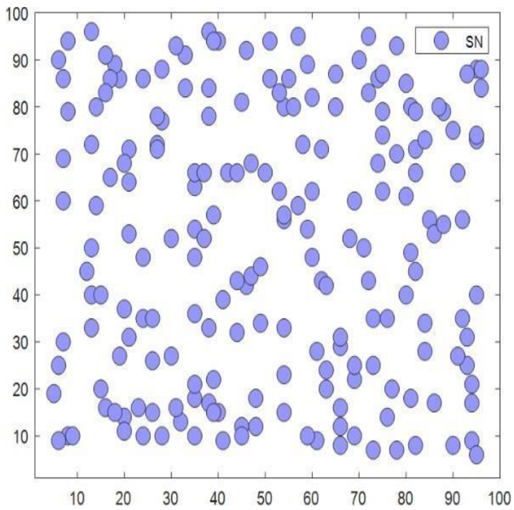


Fig.4: IoT Nodes Dispersion

All overloaded nodes nearby sink responsible for transferring the data in the network are termed as 'Hotspot nodes.' Due to unbalance between transmitting nodes, their individual energy gets lower and soon runs out of the network. This may lead to breakage of network communication. Hence, rate of dropping hot nodes as 50% has been implemented in both scenarios of the network.

The overloaded nodes have been dropped to sustain communication in the IoT network. The Fig. 5 illustrates the procedure of dropping hotspot nodes with respect to ACO iterations. The nodes nearby sink due to overload dies early. The nodes with low residual energy have been marked with brown colour. The dropped nodes have been represented using dark brown colour.

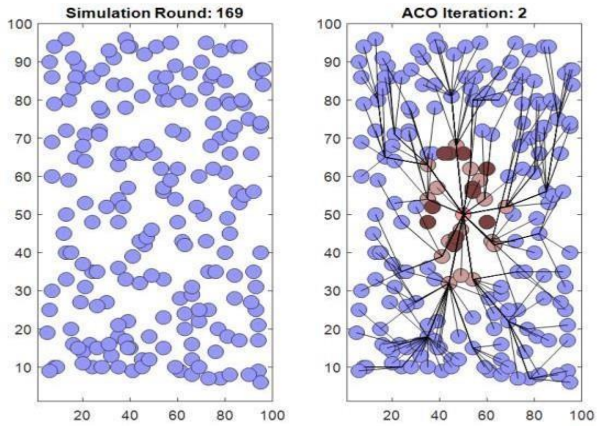


Fig.5: Dropping of Hot Nodes

Fig. 6 (a, c and e) and (b, d and f) represent individual results for the proposed techniques at i=2000 iteration for static and dynamic IoT network scenario, respectively. With the pace of number of iterations run in the simulation, the energy of the network start declining. Fig. 6 (b, d and f) highlighted deployment of communicating devices using ABMD technique. The sensor devices identify the target spot location and starts transmitting data to the sink. All initializing parameters of the network are refreshed and adjusted for improvement of the system. The number of iterations, iteration using ACO and number of ants are kept same as for both approaches. Besides this, the mobility considered as 9m/s forrealizing dynamic IoT network for ABMD routing strategy.

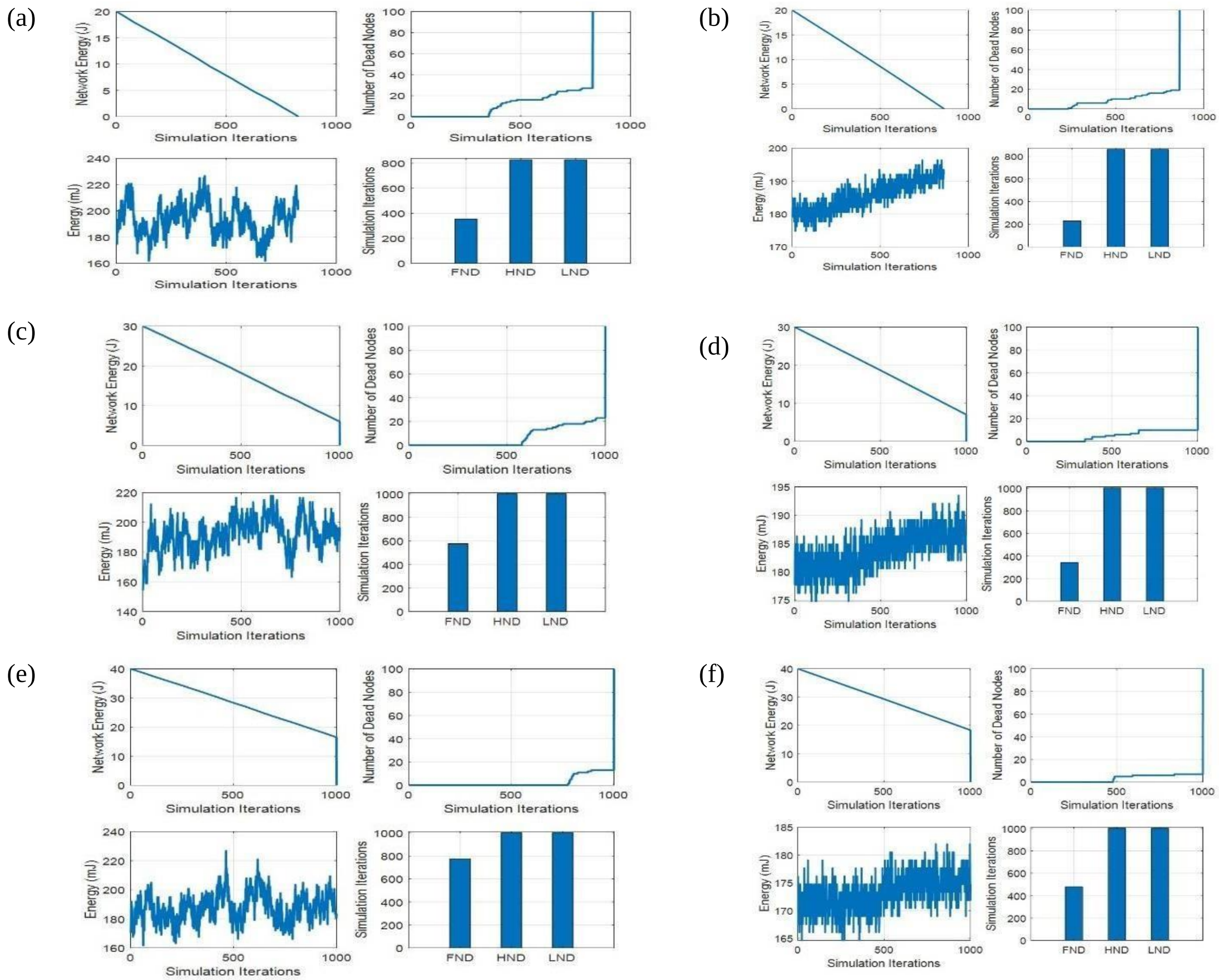


Fig.6: (a, c and e) and (b, d and f) Representation of outcomes in terms of network energy, no. of dead nodes, residual energy and lifetime of IoT network for static and dynamic network routing at 0.2J, 0.3J and 0.4J, respectively

Fig. 7 (a, b, and c) illustrates the consumption of initial energy with increase in number of simulations using a graph. Each node possesses its individual energy and it lowers down in the network respectively.

The Fig.7(a) shows that 0.2 J initial energy provided to the nodes for both approaches. At i=450, ABMD consumes 0.091 J and ABMS consumes 0.098 J. The ABMS consumes 7.14% less network energy than ABMD.

The Fig.7(b) shows that 0.3 J initial energy provided to the nodes for both approaches. At i=450, ABMD consumes 0.0195 J and ABMS consumed 0.020 J. The ABMS consumed 2.5% less network energy than ABMD. The Fig.7(c) shows that 0.4 J initial energy provided to the nodes for both approaches. At i=450, ABMD and ABMS consumed 0.0295 J and 0.0305 J energy, respectively. The ABMS has been 3.3% more energy efficient than ABMD. The network energy consumption being high in case of ABMD than ABMS approach.

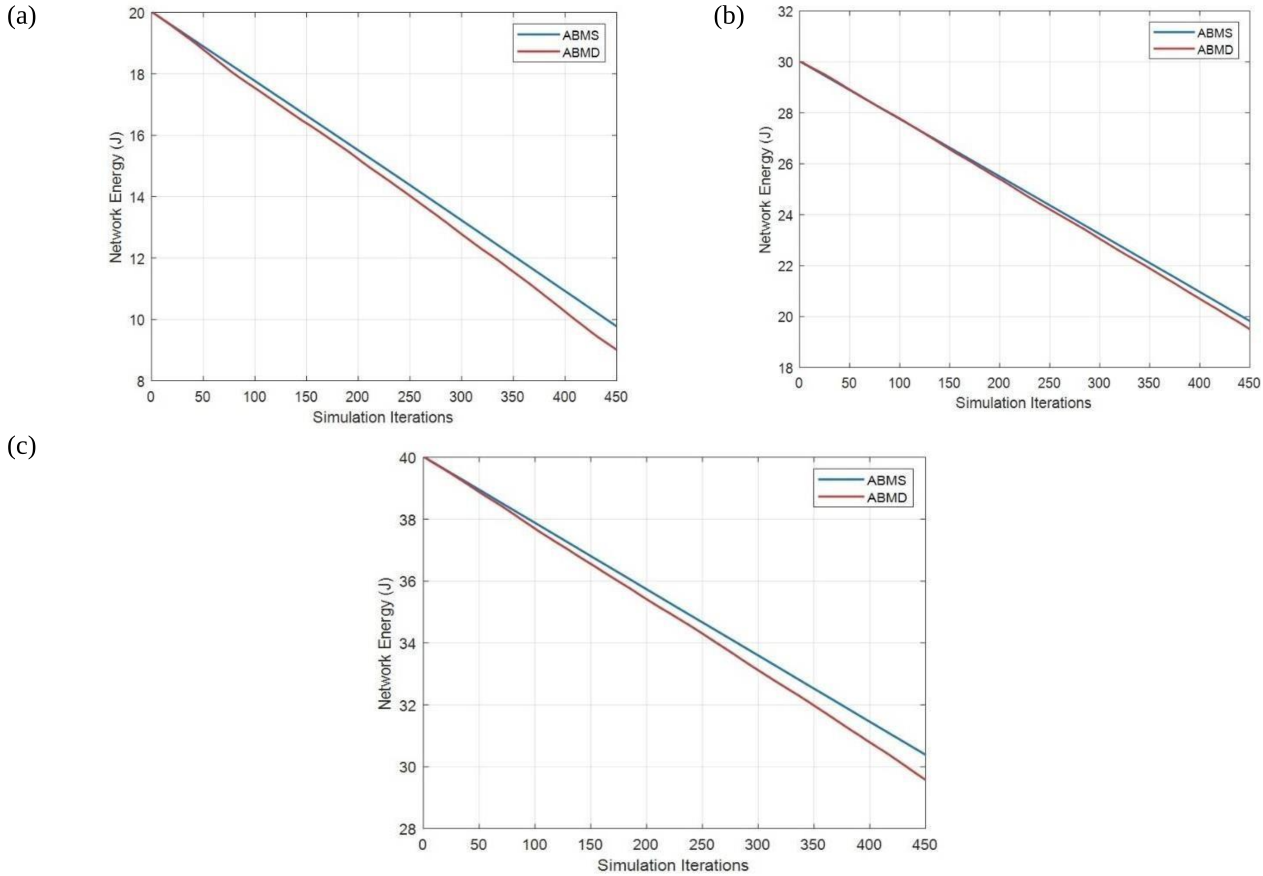


Fig.7: (a, b and c) Comparison among ABMS and ABMD, for network energy Vs simulation iterations at 0.2 J, 0.3J and 0.4J respectively.

Fig. 8 (a, b, and c) represents residual energy of ABMS and ABMD approach at varying iterations. The graph depicts ABMS routing consumes constant energy while abruptions seen implementing ABMD approach. Likewise, transmission power is distance dependent but receiving power is independent on distance. Hence, received power is always less than transmitting power. Therefore, representing residual energy in the network implementing both techniques. The constant rate of energy observed from the graph in case of ABMS. The variations in residual energy graph for ABMD depicts more energy required after every round of communication in the network. As, number of dead node increases, more energy required in the network. The increase in number of dead node count using ABMD approach. Hence, the graph is continuously raising indicating residual energy in the individual nodes for the network

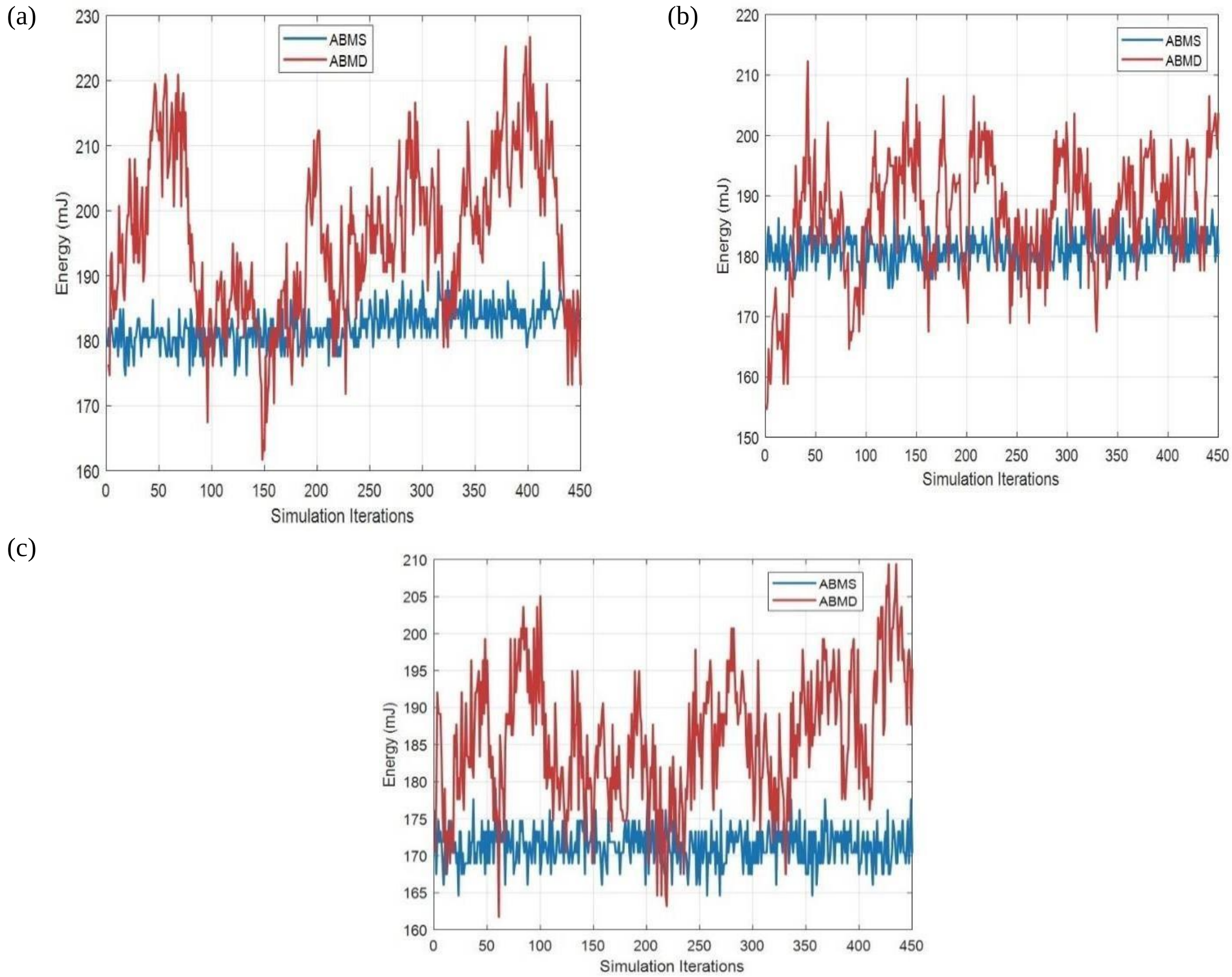
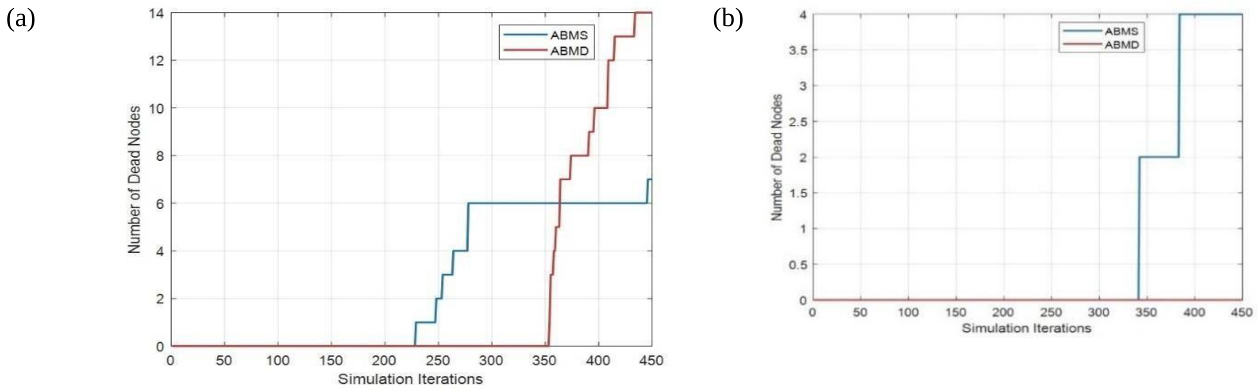


Fig.8: (a, b and c) Residual energy Vs simulation iteration comparison among ABMS and ABMD at 0.2 J, 0.3J and 0.4J, respectively

Fig.9 (a, b, c) highlight the comparison of number of dead nodes among ABMS and ABMD, for simulation iterations i=2000 at different initial energies 0.2 J, 0.3J and 0.4J respectively. The counting of dead nodes in the network being one of the outcomes for deciding the communication sustainability. The Fig.9(a) shows its first run out node at 230 round of communication for ABMS routing approach and at 350 round of communication for ABMD routing. In case of Fig.9(b) with 0.3 J initial energy, the first run out node occurs at 350 implementing ABMS routing while first dead node noticed during ABMD routing at 450. With 0.4J initial energy, no dead node count observed in the Fig.9(c).



(c)

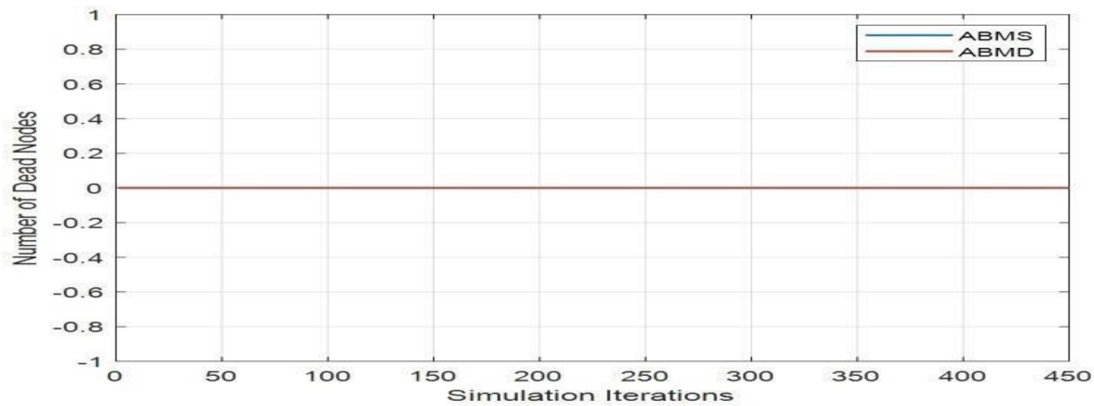


Fig.9: (a, b and c) Number of dead nodes count Vs simulation iterations comparison among ABMS and ABMD at 0.2 J, 0.3J and 0.4J, respectively.

Fig. 10 (a, b and c) represents network lifetime for the proposed techniques at 2000 iterations. The comparison of two proposed, ABMS and ABMD routing techniques have been done with above mentioned initializations for efficiency optimization in IoT. Though, network of both the approaches being different in nature. The rate of declination of energy consumed by the nodes in the network varies. With the change in initial energy (J) of the IoT network at 2000 iterations run, the stability and efficiency of different scenarios in the network varies. From Fig. 10 (a) it has been predicted that ABMS has been 5.2% more network efficient than ABMD with respect to HND (Half Node Dead) and LND (Last Node Dead). The graph from fig. 10 (b) remains equal in case ofHND and LND for both routing approaches. From Fig. 10 (c)ABMS is 77.14% more efficient in comparison with ABMD with respect to HND and LND.

(a)

(b)

(c)

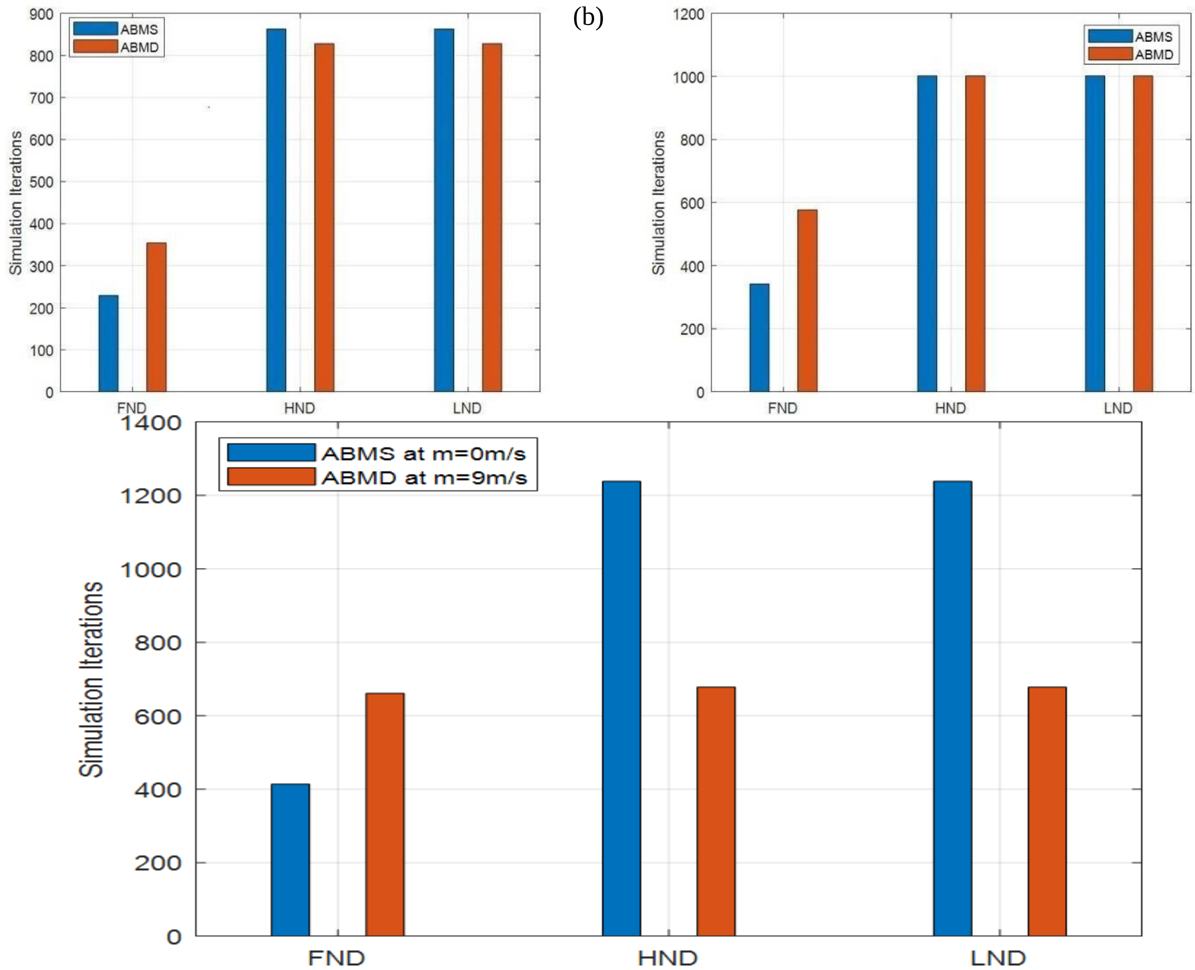


Fig.10: (a, b and c) Individual results of critical position of IoT nodes in the network for the proposed techniques at 0.2 J, 0.3J and 0.4J respectively.

The Static network being more stable and efficient as the number of alive nodes lasts longer in comparison to dynamic IoT network as revealed in Table 2. The FND (First Node Dead) is the count of nodes which run out of charging in initial stage of communication in the network. In this study, HND, LND runs out at same round specifies the communication in the network remains stable

Table 2: Number of IoT nodes in different Simulation conditions

Initial Energy (Joules)	Static IoT Network (ABMS)		Dynamic IoT Network (ABMD)	
	FND	HND, LND	FND	HND, LND
0.2	131	601	288	571
0.225	173	710	376	658
0.250	203	760	362	393
0.275	234	895	468	832
0.3	350	1000	590	1000
0.325	310	980	547	975
0.350	195	1067	610	1054
0.375	319	1127	655	844
0.4	400	1230	650	650

6. Conclusions:

The key aspect of reduction in network energy consumption and increase in network lifetime have been addressed in this work. The routing strategies, (ABMS and ABMD) have been proposed for improving network efficiency. The ABMS technique proved useful for offering an efficient communication path in the IoT network. An efficient and reliable path has been achieved using the proposed approaches.

The simulation iterations demonstrate that the ABMS algorithm finds the optimal route with better enactment and faster convergence than the ABMD method. Large-scale environments shall be investigated in the future for various IoT network situations using different optimization techniques. Multiple types of distances could also be incorporated between two nodes of the network.

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