A Parallelly Implemented Hybrid Multi-Objective Efficient Persuasion of Coverage and Redundancy Programming Model for Internet of Things in 5G Networks using Hadoop

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Abstract – In 5G networks, the demand for IoT devices is increasing due to their applications. With the development and widespread adoption of 5G networks, the Internet of Things (IoT) coverage issue will collide with the issue of enormous nodes. In this paper, a parallelly implemented Hybridised Mayfly and Rat Swarm Optimizer algorithm utilising Hadoop is proposed for optimising the IoT coverage and node redundancy in IoT with massive nodes, which automatically lengthens the IoT's lifecycle. Initially, parallel operation divides the IoT coverage problem involving massive nodes into numerous smaller problems in order to reduce the problem's scope, which are then solved using parallel Hadoop. Using the flight behaviour and mating process of mayflies, we optimise the coverage problem here. Rats' pursuing and attacking behaviours are employed to optimise the redundancy problem. Then, select the non-critical nodes from the critical nodes in an optimal manner. Lastly, parallel operation effectively resolves the IoT's coverage issue through massive nodes by strategically extending the IoT's lifespan. Using the NS2 application, the proposed method is simulated. Computation Time, Energy efficiency, Lifespan, Lifetime, and Remaining Nodes are analysed as performance metrics. The proposed MOP-Hyb-MFRS-IoT-5GN method achieves lower computation times of 98.38%, 92.34%, and 97.45%, higher lifetime of 89.34%, 83.12%, and 88.96%, and lower remaining time as 91.25%, 79.90%, and 92.88% compared with existing methods such as parallel genetic algorithm spread the lifespan of internet of things on 5G networks (MPGA-IoT-5GN).

Keywords – Mayfly and Rat Swarm Optimization Algorithm, 5G Networks, Hadoop, Multi-Objective Programming, IoT Coverage, Node Redundancy.

I. INTRODUCTION

The application of IoT faces new opportunities, challenges, development, and dissemination of 5G networks [1]. Sensor nodes in IoThabitually interrupted by the power sources. Hence, encompassing the IoT lifespan is always an acritical problem [2]. Connect extra sensor nodes in the monitoring area and allow these nodes alternately active/slumber and this is the most conceivable approach to resolve this problem [3].5G networks practice a high-frequency and short-range radio for communicationthat attains maximal transmission speed [4]. Because of this, 5G networks stretch the amount of base station that is associated with using 4G networks. At 4G networks, every base station (BS) is comprised of a network access server responsible [5]. Frequently, accessing the network server works at the entrancefor achieving indigenous IoT [6]. Conversely, diminishing the production cost5G network shortens the network access server under BS [7]. In its place, it takes charge of such network access servers [8]. Therefore, the data center accomplishes enormous IoT which consists of numerous local internet of things and encompasses huge nodes [9]. In the meantime, the 5G network encourages the approval of IoTand results inthe additional device of IoT[10]. Using the growth and popularization of 5G networks, the submission of IoT faces new opportunities and challenges [11]. Sensor node in IoT often has nocontinuous power sources. Thereforespreading the IoT lifespan is an important problem. There contains only one possible way for solving the power source issue is to overlap extra sensor nodes inthe monitoring area [12]. A confirmation of employed nodes onIoTlasts one timeframe. Then, another node on subsequent confirmation turns active for the alternate timeframe [13]. Consuming worker nodes, the configuration continues to build a sequence until IoT dissipates the sensor nodes and the residual nodes cannot reach the lower limit of IoT coverage. [14]. Hence, IoT lifespan is the same for lengthy configuration arrangements in working nodes. In 5G networks, a sequence of optimal configurations is calculated to spread the lifespan of IoT to encounter massive-node problems [15].

The IoT coverage problem is the selection issue for nodes of coverage-centric dynamic that is previouslyan NP-complete problem, resolves difficult massive-node situations habitually away from resolving the capability of the existing algorithm [16]. Frequently, these algorithms require reserving a series of probable solutions on solving method examine the global optimal solutions [17]. In the massive-node consequences, a count of possible solutions is needed to solve the huge process. This algorithm fails due to the incapability of the calculation after a longer period.Three requests are existent for the algorithm to be accomplished to resolve the IoTcoverage problem in massive-node scenarios.Initially, this algorithm is capable of damaging the scales and ensures to completionof the computing operation that is surrounded by the restricted periods. Moreover, resolving the IoTcoverage problem as a multi-objective programming issue [18]. Therefore,the algorithm must take network coverage and node severance into account and deliberate the influence of present configuration working nodes under subsequent configuration. At last, the algorithm needs interior optimization resolving process may rapidly change in the direction of possible solutions.

Motivation behind This Research Work:

The Internet of Things coverage challenge is a comprehensive selection problem for coverage-centric active nodes that is frequently beyond the capabilities of current algorithms to address massive-node systems. To find the global best answer, the algorithms in use must typically reserve a set of alternate solutions. To finish the solving process in large-node setups, a massive amount of feasible solutions are required. The process will fail because it will run out of time before completing the calculation. As a result, to tackle the IoT coverage problem in massive-node scenarios, the algorithm must meet three important conditions.

First and foremost, the approach should be capable of condensing the size of the problem while yet finishing the com putation on time.The Internet of Things coverage challenge is also a multi-objective programming problem.

- Third, internal improvement of the algorithm is required so that the solving process can progress quickly towar d usable answers [28, 29].
- As a result, the algorithm should assess network coverage and node redundancy, as well as the impact of the pre sent working node configuration on the subsequent configuration.

The major contributions are summarized below:

- In this manuscript, a parallelly implemented Hybridized Mayfly and Rat Swarm Optimizer algorithm using Hadoop (MOP-Hyb-MFRS-IoT-5GN) is proposed.
- Initially, parallel operation splits the coverage issue of IoT using massive nodes into numerous smaller issues to degrade the problem scale, and solve by utilizing the parallel Hadoop.
- Here the coverage problem is optimized using the flight behavior and mating process of mayflies [19].
- The redundancy problem is optimized using the chasing and attacking behaviors of rats [20]. Then, optimally select the non-critical nodes from the critical nodes.
- Finally, parallel operation effectively solves the coverage issue of the IoTusing huge nodes by pointedly spreading thatIoT lifespan. The proposed method is simulated using the NS2 tool.
- The performance metrics like IoT Lifespan radius Vs Computation Time, IoT Lifespan radius Vs Energy efficiency, IoT Lifespan radius Vs Lifespan, IoT Lifespan radius Vs Lifetime, and IoT Lifespan radius Vs Remaining Nodes are analyzed.
- Then the efficiency of the proposed EESS-CRN–GRFOA-BJA method is compared with the existing method such as parallel MPGA-IoT-5GN [21], EDTC-GCN-IoT-5GN [22], and CRAN- IoT-5GN [23].

II. LITERATURE SURVEY

Various research works extend IoT lifespan. Some recent research works are reviewed below,

In 2020, Zhang, et.al., [24] presented anMPGA-IoT-5GN. In this, the designed parallel genetic algorithm split that coverage issue for the IoT using massive nodes into various smaller problems. Then, resolves these issues using Hadoop in parallel. To destroy the scale of large IoT, initially, the algorithm utilized for partitioning and grouping the operation makes the coverage problem resolvable. The multi-objective programming-based genetic algorithm (MPGA) resolved the coverage problem. For optimizing the IoT coverage and node redundancy, MPGA uses faster non-dominated sorting. As a final point, the parallel genetic algorithm utilizes individual pruning and a uniform mutation internally improves the genetic algorithm and strengthens the resolving procedure for rapidly converging toward the feasible solution. The suggested technique transmits a higher amount of data conversely the amount of energy consumption from one node to another node was maximized for transmission.

In 2020, Yan, et.al., [25] presented an Energy Efficient Topology Control (EDTC) algorithm to optimize the ad-hoc wireless lifetime of IoT networks on 5G, and B5G. This work focused on balancing node residual energy and node grade to prolong network life. In this, a statistical-based algorithm for assessing the network topology further developed an

EDTC. The energy efficiency topology control influences the supreme spanning tree algorithm to build a vigorous backbone topology to develop the presented energy efficiency ratio algorithm to re-advertise particular edges of the topology. In random communication experimentation, the presented EDTC algorithm attains twice the lifetime of the network than the state-of-the-art. The suggested technique reduces the size and amount of data transmission. It is not appropriate for the entire measurement environment.

In 2019, Agiwal et al [26] presented the 5G-enabled internet of things. In this, the Internet of Things (IoT) offers development in the quality of life while introducing new business avenues. A combined effort of researchers, industries, manufacturers, service providers, and other stakeholders is necessary to address the various IoT requirements. This convergence is predictable to unleash a new dimension of opportunities that cannot be completely realized using conventional solutions. In this sense, the technical details of the developing 5G networks are in line with the pressing requirements of IoT, necessary for the ultimate configuration of a connected life. We also outline the restrictions of legacy networks to meet the peculiarities of IoT requirements.

In 2021, Mao et al [27] presented the energy-efficient computing and communications mechanisms ofIIoT systems (like smart grids). When accepted in industrial and manufacturing settings, IoT known as Industrial IoT (IIoT) has involved growing research attention. Energy efficiency is the most significant research topic on green IIoT as 1) restricted resources may considerably affect the lifetime of IIoT systems and 2) massive sensors and devices; the machines continue to consume a considerable amount of energy and increase the carbon footprint. The experimental result provides a longer calculation time and higher energy efficiency.

In 2018, Cao et al [28] presented the real-time approximate adaptive calculation of QoS for lifespan optimization of mobility-aware IoT. In this, the presented method is made up of offline and online stages. In the offline stage, an optimal mobility-aware task program is obtained that maximizes the lifetime of the network with the mixed-integer linear programming (MILP) technique. Redundant executions based on overlapping of a single task on different IoT devices due to mobility to save energy are avoided. In the online stage, a time-efficient and guaranteed throughput QoS adaptive heuristic was established based on a cross-entropy system to adapt task execution to fluctuate QoS requirements. Extensive simulations depending on synthetic applications and real-life benchmarks have been executed to authenticate the efficiency of the presented scheme. It provides lower computational time and a lower lifetime.

To enhance IoT coverage, some academics have developed several meta-heuristic algorithms, as indicated in **Table 1.**

Table 1. Literature survey

Name of the Algorithm	Technology	Main findings or conclusion relevant to the proposed research work	Remarks
Parallel Genetic Algorithm [30].	Genetic Algorithm.	In this, the designed parallel genetic algorithm split that coverage issue for the IoT using massive nodes into various smaller problems. Then, resolves these issues using Hadoop in parallel.	The amount of energy consumption from one node to another node was maximized for transmission.
An energy-efficient topology control algorithm for optimizing	EDTC	This work focused on balancing node residual energy and node grade to prolong network life.	The suggested technique reduces the size and amount of data transmission. It is not appropriate for the entire measurement environment.
A Hybrid Technique Based on a Genetic Algorithm for Fuzzy Multiobjective Problems in 5G, Internet of Things, and Mobile Edge Computing.	Improved Technique based on GA	An improved technique based on GA resolves the multi-objective optimization problems (MOOPs) denoted by constraints of fuzzy relation using normal.	The presented approach increases the lifetime of the network but it produces high overhead for data transfer
Mobile wireless sensor networks coverage maximization by firefly algorithm,"	Firefly Algorithm	Expand the reach of mobile IoT	This method achieved better coverage with less energy loss or with minimal displacement. but fitness functions for this multiobjective problem can be used and WSNs with several mobile sensors can be considered

In 2021, Shafiei, et.al., [29] presented a hybrid method based on a genetic algorithm for fuzzy multi-objective problems on 5G, IoT, and mobile edge computing. Here, an improved technique based on GA resolves the multi-objective optimization problems (MOOPs) denoted by constraints of fuzzy relation using normal. Therefore, initially to diminish the size of the problem several techniques were used, so that the reduced problems were resolved effortlessly. The presented GA-based method is smeared the resolving condensed problem locally. Furthermore, several experiments are accompanied to display the competence of the presented approach. The suggested method overcomes the weaknesses of conventional methods owed to their capacities onthe non-convex feasible domain, similarly valuable to model complex systems. The presented approach increases the lifetime of the network but it produces high overhead for data transfer.

III. PROPOSED METHODOLOGY

In this manuscript, a parallelly implemented Hybridized Mayfly and Rat Swarm Optimizer algorithm (MOP-Hyb-MFRS-IoT-5GN) using Hadoop is proposed for calculating the optimum configuration structure for IoTwithhuge nodes that extend theIoTlifespan. The block diagram of the proposed MOP-Hyb-MFRS-IoT-5GN method is given in **Fig 1.**

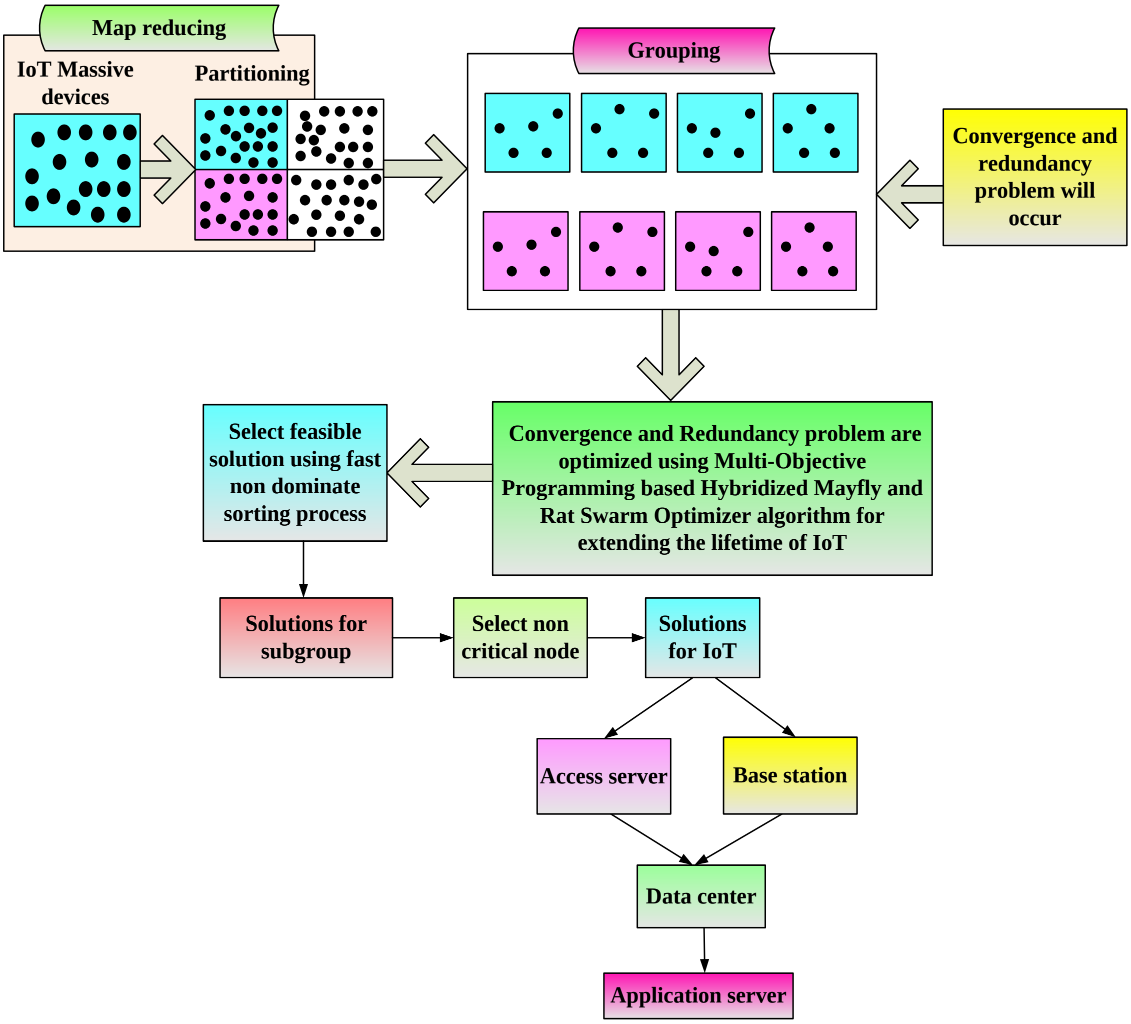

Fig 1. Block diagram of proposed MOP-Hyb-MFRS-IoT-5GN method

The detailed discussion regarding the Parallelly Implemented Hybrid Mayfly and Rat Swarm Optimizer algorithm for Multi-Objective efficient persuasion of Coverage and redundancy Programming model for IoT in 5G Networks using Hadoop are given below,

The IOT devices consist of a large number of nodes from these nodes some of the nodes are critical and some other nodes are non-critical. Here, the critical nodes affect the non-critical, so the networks are affected byconvergence and redundancy problems in the IOT devices.

The Network coverage problem is one of the important problems for constructing IoT devices and the values of the coverage must be increased or it must be more than the given threshold value. By maximizing the coverage area, the needs of IoT become guaranteed in the quality of the services (QoS). The IoT coverage model is formulated below:
If an IoT Device works in the monitoring area X and its area is represented as the $n \times m$ grids, every grid is $1n \times 1n$. Let r_i be i^{th} sensor nodes, num specifies the count of a node in IoT, $R = (r_1, r_2, ..., r_i, ..., r_{num})$ and specifies the sensor node set. Then, the position of every node is represented as the (a_i, b_i) stands of the coordinate of r_i the node, the rand (a_i, b_i, s) denotes the actual perception circle of r_i the node. Where, node $r_i(a_i, b_i)$ specifies center, s specifies radius. Assuming the communication radius s_d at least 2 times as the perception radius s, that is, $s_d \geq 2s$.In this manner, sensor nodes coverthe monitoring part, and IoT maintains its connection. Let the connectivity is represented as the $Q_{\text{cov}}(a, b, r_i)$ bethe conditionsthat sensor node $r_i(a_i, b_i)$ cover the grid (a, b) that is expressed in equation (1).

$$Q_{\text{cov}}(a, b, r_i) = \begin{cases} 1, & (a - a_i)^2 + (b - b_i)^2 \leq s^2 \\ 0, & else \end{cases} \tag{1}$$

$$Q_{\text{cov}}(a, b, r_i) = \begin{cases} 1, & \ni r_i \in D_j, Q_{\text{cov}}(a, b, r_i) = 1 \\ 0, & else \end{cases} \tag{2}$$

Furthermore, let $Q_{\text{cov}}(a, b, D_j)$ be the conditions that j^{th} working nodes configuration (a, b) covering the grid, Here D_j specifies the subset node of set R denotes all working nodes and this values is expressed in equation (2). A node r_i once goes to j^{th} working node configuration,then the node r_i satisfiesthe equation (1) and IoT covers (a, b) monitoringof grids. Let $X_{area}(D_j)$ specifies the grid count that covers D_j configurationand it is expressed below,

$$X_{area}(D_j) = \sum_{a=1}^{n} \sum_{b=1}^{m} Q_{\text{cov}}(a, b, D_j) \tag{3}$$

Therefore the convergence problem in the IoT devices with a coverage rate of j^{th} working nodes configuration $S_{\text{cov}}(D_j)$ specifies grid count that is covered by the working nodes configuration D_j by dividing the total count of grids in the monitoring area and its equation is given in equation (4)

$$S_{\text{coverage}}(D_j) = \frac{\sum_{b=1}^{n} \sum_{b=1}^{m} Q_{\text{cov}}(a, b, D_j)}{n \times m} \tag{4}$$

Then the redundancy is calculated using equation (5)

$$S_{redudancy}(D_j) = \frac{\sum_{a=1}^{n} \sum_{b=1}^{m} Q_{red}(a, b, D_j)}{n \times m} \tag{5}$$

Using equation (5), the rate of redundancy is measured. Above mentioned terms are equally exclusive, and their single objective function corresponds to the optimal solution said to be unidentified. The critical node is considered the sensor node that is needed for various possible solutions. Then the redundancy with configurations is given in equation (6)
The coverage rate shall not go below the cutoff point, to provide Quality of Service (QoS),If active nodes in the Dj arrangement redundantly cover the grid, then let Qred (a, b,Dj) be the condition (a; b).

$$Q_{red}(a, b.D_j) = \begin{cases} 1, & C_{\text{cov}}(a, b, D_j) > 1 \\ 0, & else \end{cases} \tag{6}$$

Here equation (4) and (5) represents the coverage and redundancy problem in the IoT devices and these problems are minimized using the Hyb-MFRS algorithm.

Then solving the coverage issue in parallel is feasible for IoT using massive nodes on 5G networks is difficult. The problems of the IoT are, initially, the perception area of a sensor node is much lesser thanthe monitoring area of an IoT, and that is if the node is active it only affects the local area instead of the entire world. Therefore, it is feasible to divide the IoT into many zones (i.e. sub-IoT) and solve their coverage problems in parallel. Second, IoT has numerous redundant nodes under over-deployment and alternate node activation scenarios. The above problems are solved using the Hybridized Mayfly and Rat Swarm Optimizer Hyb-MFRS algorithm and it is proposed to increase the lifetime of IoT using massive nodes on 5G networks.

Parallelly implemented Hybridized Mayfly and Rat Swarm Optimizer algorithm

Here the Hybridized Mayfly and Rat Swarm Optimizer algorithm implemented in parallel is used to spread the lifespan of IoT using massive nodes on 5G networks. As the data center in 5G networks takes over the functions of the access servers under base stations, it manages the great IoT that is made up of multiple IoTs equivalent to base stations. The data center outfits partitioning operations to divide the huge IoT into several sub-IoTs. The data center then performs clustering operations on every sub-IoT if the sub-IoT still has numerous nodes. At last, the algorithm adopts a non-critical node preferential selection approach to regulate the current configuration of the worker nodes. This job applies Hadoop to compute worker node configurations for every group of nodes in parallel. The current configuration of worker nodes as feasible solutions should evade chosen critical nodes. If these critical nodes lose power prematurely, the last configuration will not be able to influence the lower limit of coverage based on the lack of critical nodes. Then, to separate the critical nodes from the IoT devices and compute the worker node configurations for each group of nodes in parallel, the Hyb-MFRS algorithm is used.Hyb-MFRS algorithm is the combination of the Mayfly optimization algorithm and the Rat swarm optimization algorithm.

The mayfly optimization algorithm can solve the optimization issues using flight behavior and the mating process of mayflies and it combines the main benefits of swarm intelligence and evolutionary algorithms.Rat Swarm optimization algorithm can solve challenging optimization problems using the chasing and attacking behaviors of rats it combines the main benefits of swarm intelligence and evolutionary algorithms. Combing the flight behavior and the mating process of mayflies and chasing and attacking behaviors of rats are used to solve the coverage and redundancy problems in IoT devices.

Mapping-Reduce Process in Parallelly implemented Hybridized Mayfly and Rat Swarm Optimizer algorithm

Mapping-Reduce Process is used to split a large number of IoT mass devices into sub-nodes for separating the critical and non-critical nodes by the process of partitioning and grouping using the Hyb-MFRS algorithm. First of all, the flight behavior of the Mayflies calculates the size of the sub-IoT from the massive devices and then partitioned into numerous sub-IoTs. At the same time, the size of every sub-IoT is ten times lower than the radius of the perception, and the nodes in the adjacent sub-IoT consist of apparent influence on the coverage of the current sub-IoT. Alternatively, a large-sized sub-IoT that has numerous nodes will lead to a fast increase in performance time. Therefore the flight behavior of the mayflies will optimize the coverage problem duringthe partition process and the mating process of the mayflies will reduce the execution time by using the parameter M_{sub} , Where, M_{sub} which represents the count of sub-IoT partitioning.

Secondly, the chasing and attacking behaviors of rats are used to solve the grouping problem in the massive IoT devicesand to reduce the redundancy problem for selecting critical nodes from the non-critical nodes. Let M_{grp} is represented as the number of nodes present in the grouping operations of the sub-IoT of the Hyb-MFRS algorithm. Here the chasing behavior of the rat swarm algorithm divides the nodes into the sub-IoT into M_{grp} groups till the grouping operations are stopped. Then randomly distribute the nodes into the sub-IoT. Here, M_{time} specifies times of grouping operations. While applying the Hyb-MFRS the time forms $M_{time}+1$ specify times of grouping operations to produce extra groups to cover feasible solutions, if other optimal solutions exist after M_{time} times of grouping operations.

The fitness functions of the Hyb-MFRS algorithm are used to maximize the coverage area of IoT devices by removing critical nodes from the non-critical nodes and minimizing the redundancy problem. Here the coverage problem is optimized using the flight behavior and mating process of mayflies and the redundancy problem is optimized using the chasing and attacking behaviors of rats. Then the fitness equation for attaining the objective function equation is given in equation (7)

$$Fitness\ \ function(objective) = Max(IoT\ \mathrm{cov}\,erage), Min(\mathrm{Re}\,dudancy) \tag{7}$$

Then the detailed explanations of the Hyb-MFRS Algorithm for solving coverage and redundancy problems during partitioning and grouping while separating critical nodes from a non-critical node for increasing IoT lifetime.

Multi-Objective Programming-Based Hyb-MFRS Algorithm

In this, the parallel algorithm Hyb-MFRS based on multi-objective programming first splits the IoT using massive nodes into several sub-IoTs. The algorithm performs pooling operation times for the nodes in each sub-IoT to cover feasible solutions. In this way, the algorithm gets a set of node groups that the Hybridized Mayfly and Rat Swarm Optimizer algorithm may deal with. With partitioning and pooling, the algorithm maps the coverage problem for IoT with massive nodes into numerous small problems.**Fig 2** portraysthe flow chart for Hybridized Mayfly and Rat Swarm Optimizer algorithm for solving coverage and redundancy problems. Then for solving coverage and redundancy problems during partitioning and grouping Multi-Objective Programming-Based Hyb-MFRS Algorithm is used. Multi-Objective Programming consists of two phases Hyb-MFRS Algorithm and fast non-dominated sorting for optimizing coverage and redundancy problems and especiallythe selection of non-critical nodes. The critical node is considered the sensor node that is needed for various possible solutions.

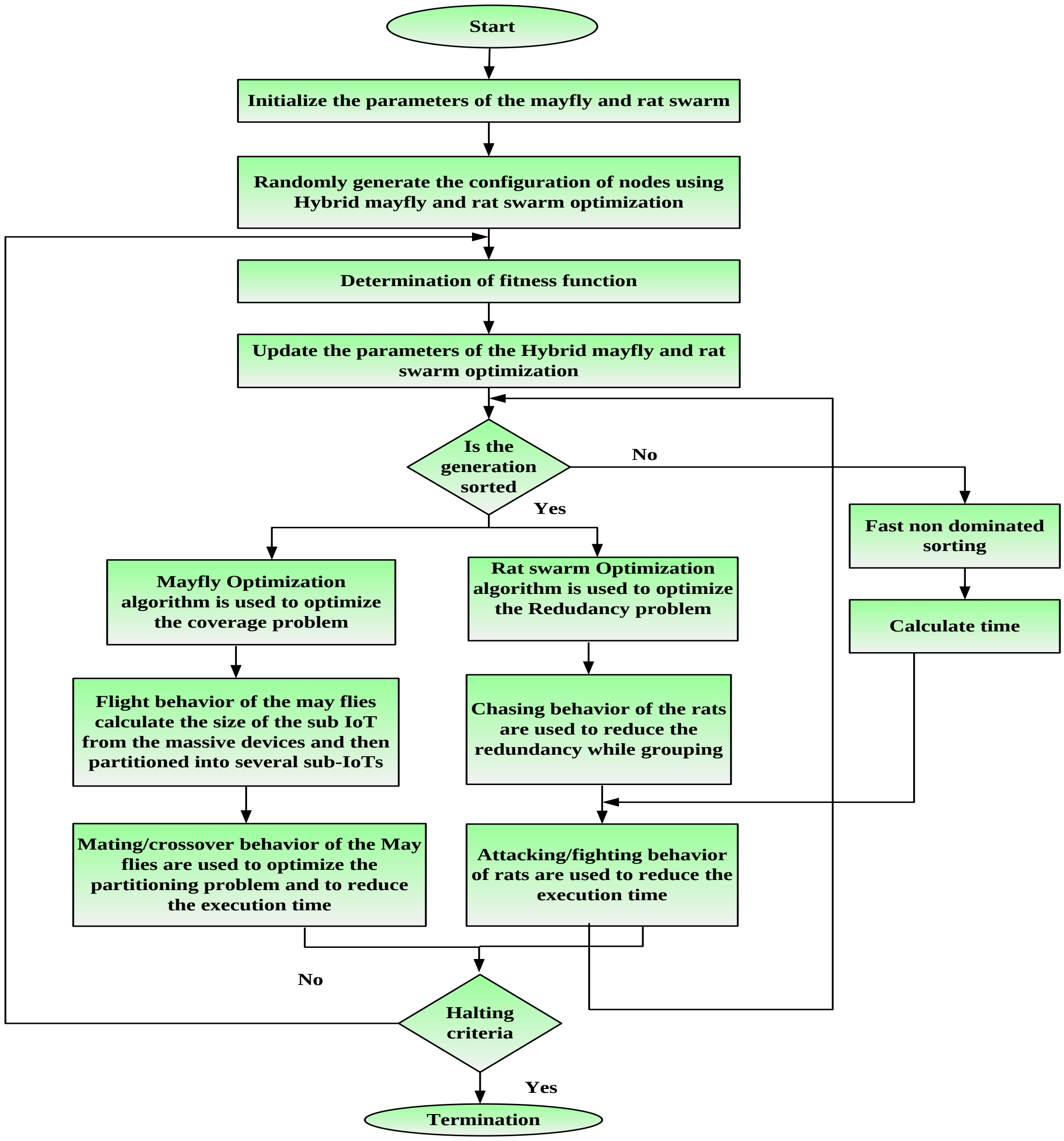

Fig 2. Flowchart for Hybridized Mayfly and Rat Swarm Optimizer algorithm

Ifthe algorithm determines the present configuration of working nodes from the possible solution, it avoids the selection of critical nodes. Hence, $M_{config}(D_j)$ specifies the count of critical nodes in D_j configuration. Multi-Objective Programming based Hybridized Mayfly and Rat Swarm Optimizer has to minimize $M_{config}(D_j)$ .Here the coverage problem is optimized using the flight behavior and mating process of mayflies. The flight behavior of the mayflies calculates the size of the sub-IoT from the massive devices and then partitioned into several sub-IoTs. At the same time, every sub-IoT is ten times lower tothe radius of the perception, and the nodes in the adjacent sub-IoT consist of apparent influence on coverage of current sub-IoT using parameter M_{sub}. The current positions of the may fly is j^{th} a configuration of the partitioning of sub-IoT. Then the coverage problem minimization equation is given in equation (8)

$$M_{best_j} = \begin{cases} M_{sub}^{time+1}, & if\ D\left(M_{sub}^{time+1}\right) < D\left(M_{best_j}\right) \\ is\ kept\ the\ same, & otherwise \end{cases} \tag{8}$$

Then the mating or the cross-over behavior of the Mayflies is used to optimize the partitioning problem and to reduce the execution time, therefore easily selecting the critical nodes from the non-critical nodes. The crossover operator signifies the mating process among two mayflies as follows: one parent is chosen as the male population and the female population. Here many flies are represented as the nodes, here two types of nodes are selected male for critical nodes and female for non-critical nodes and optimally select the best nodes to select new nodes as offspring the selection of critical and non-critical nodes are given in the equation (9)

$$\begin{aligned} Newnode_1(off\ spring) &= D * critica\ln ode + (1-D) * noncritical \\ Newnode_2(off\ spring) &= D * noncritica\ln ode + (1-D) * critical \end{aligned} \tag{9}$$

Here D is represented as the random values with configurations, in this way coverage problem is optimized and optimally selects the critical nodes from the non-critical nodes. Secondly, the chasing and attacking behaviors of rats are used to solve the grouping problem in the massive IoT devices and to reduce the redundancy problem for selecting critical nodes from the non-critical nodes. Let M_{grp} is represented as the number of nodes present in the grouping operations of the sub-IoT of the Hyb-MFRS algorithm. After selecting the critical nodes from the non-critical nodes the nodes are to be grouped, while grouping redundancy problem will occur in the system, that will reduce the performance and the time is increased. The chasing behavior of the rats is used to reduce the redundancy while grouping and its equation is given in equation (10)

$$M_{grp} = S_{red} - j \times \left(\frac{S_{red}}{Iteration_{\min imization}} \right), Where\ \ j = 0,1,2,...iteration_{\min imization} \tag{10}$$

In this way, the redundancy is minimized and the execution time is reduced using the fighting behavior of rats. When more packets are entering the IoT devices delay will occur in the system so the time is increased for identifying the nodes, here time is reduced using the equation (11)

$$(M_{time} + 1)_j = \left| M_{time}(j) - M_{time} \right| \tag{11}$$

By using equation (11) the execution time is reduced and the objective function is satisfied using equations (8-11) therefore coverage area is maximized and redundancy is reduced during the partitioning and grouping process.

Fast Non-Dominated Sorting

The Hyb-MFRS-fast non-dominated sorting adoptsthe fast non-dominated sorting algorithm for optimizing the coverage and redundancies. Suppose a_1 and a_2 exist. Then, a_1 dominate a_2, a_1 is superior to a_2 every objective. If the a_1 solution doesn't dominate any of the other solutions calleda non-dominated solution. The fast non-dominated sorting algorithm executesthe multi-objective programming by non-dominated set search. Let m_q and MR_q specifies the count of solutions by dominates the present q solution and a solution set isdominated by the present q solution. Then, fast non-dominated sorting computes the m_q value and MR_q specifies every individual. Especially, fast non-dominated sortinglikens the coverage and redundancies of individualsinthe present generation find every individual whose MR_q is equal to 0.

Merging Solutions for Total IoT

AParallelly implemented Hyb-MF-RS algorithmuses FNS for merging the solutions as smaller node groups and sub-IoT.To search,FNS reserves all non-dominated solutions. A non-dominated solution has either greater coverages/lesser redundancies compared with any other solution. Let M_{feas} represents the count ofpossible solutions reserved nextto FNS. Whenparallel algorithm achieves $(M_{time}+1)$ times groups of operations of a node on everysub-IoT constitutes $(M_{time}+1)\times M_{grp}$ groups. So it solves groups using Hadoop in parallel. Therefore, the algorithm collects the possible solution for $(M_{time}+1)\times M_{grp}$ the group in the iteration part. Then, the algorithm sortingthe solution uses fast non-dominated sorting and retains the 1st M_{feas} solution.Ifthe count is lesserthan that M_{feas}, each solution is reservedto be the new solution set. Also, the algorithm gathers the leftover solutions M_{grp} group as a testing set. Then, the algorithm combines the test set into the solution set uses the comparing solution sets.Next, combine 2 sub-IoT by generating thefinal solution set to the whole IoT.Exactly, the algorithm combines the possible solutions from the 2adjacent sub-IoT forcalculating the Cartesian product. Merging solutions for Total IOT is shown in **Fig 3.**

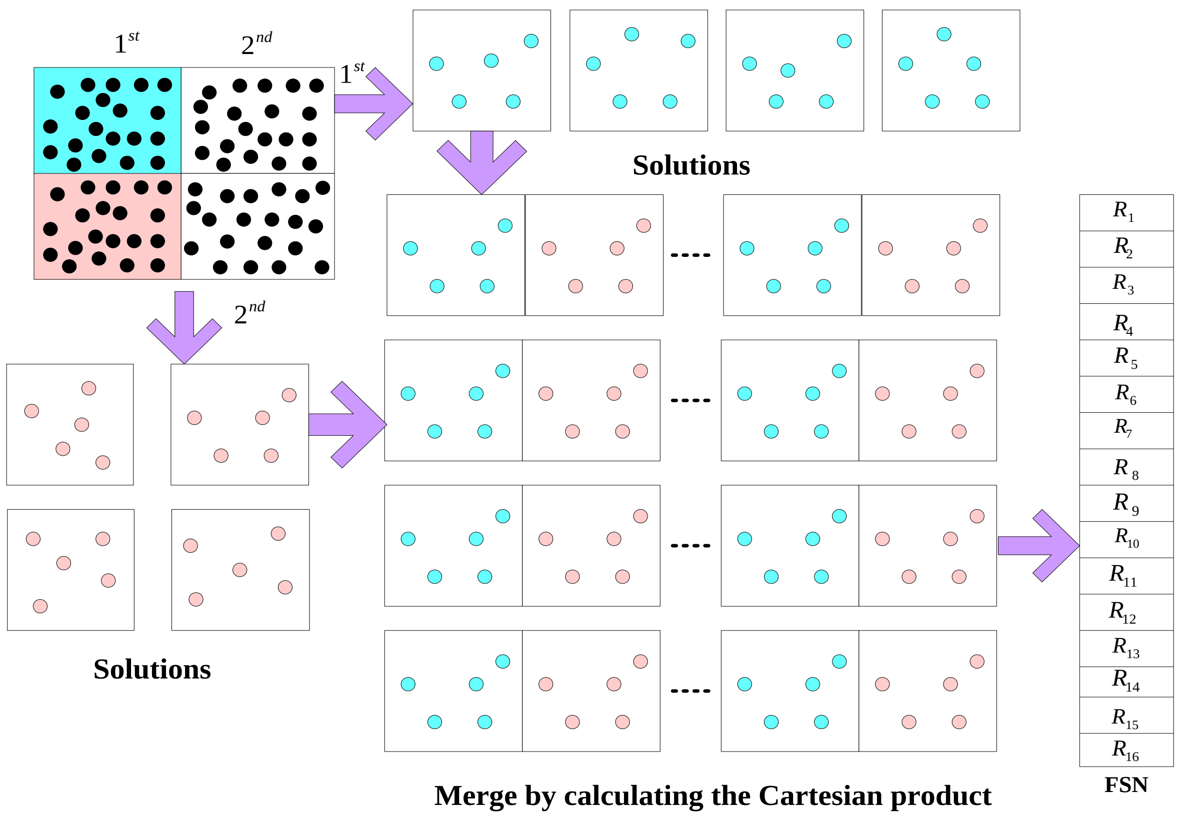

Fig 3. Merging solutions for Total IOT

The algorithm sort's thesolution using FSN and extracts 1st M_{feas} solution as a solution set with combined IoT by the2sub- IoT. The algorithmgetsthe 16 solutions for combined IoT forcalculating Cartesian products. Lastly, the algorithm sorts the solution using FSN and retain the 1st6 solutionsconsider for the set of solution. The process continues merging stillevery sub-IoT ismergedinto IoT. Then, this algorithmattainsa solution set to the whole IoT.

Preferential Selection of Non-Critical Nodes

The parallel algorithm accepts 2nd section of MOP-Hyb-MFRS (that is the preferred selection of non-critical node) for determining the present working node configuration. Considering the process affects the present configuration in the subsequent configuration. Also, it diminishes the counts of dangerous node requirements. When the incidence counts of nodes rise the threshold sets the node to a critical node. When parallel algorithm combines the solution to the whole IoT and sorting solutions which is already created according to the coverage and redundancy. Every generated solution contains MOP-Hyb-MFRS integrate into the number of critical nodes. Dangerous nodes are distributed in the middle of the monitoring part. Therefore, MOP-Hyb-MFRS identify the critical nodes accurately. Then, the selected configuration well satisfythe3 goals, these are coverage, redundancy, minimize the critical nodes. Consequently, Hyb-MFRS is maximizing length in the working nodes' configure the order extends the lifespan of IoT.

IV. RESULTS AND DISCUSSION

Here, the simulation performance of a parallelly implemented hybrid (MF-RS) multi-objective efficient persuasion of coverage and redundancy programming model for IoTs in 5G networks using Hadoopis proposed. The proposed scheme is implemented in NS2, Intel i5 CPU, and 4GB memory. Here, evaluation metrics like computation time, energy efficiency, lifespan, lifetime, and remaining nodes are analyzed. The performance metrics like efficiency, computation time, energy efficiency, lifespan, lifetime, and remaining nodes are analyzed. These metrics in the proposed system are compared with the 3 existing methods. The 3 existing methods are MPGA-IoT-5GN [21], EDTC-GCN-IoT-5GN [22], and CRAN- IoT-5GN [23]. The parameters utilized in the simulations show in **Table 2.**

Table 2. Simulation parameters

Simulation parameters	values
Monitoring area	$100m \times 100m$
Coverage bound	90%
Count of nodes	25
Perception radius	10m
Energy units in a node	10
Individual numbers in a generation	60
Maximum generations	100

Evaluation Metrics

In this, different performance measures are used to calculate the results. The performance metrics are calculated as follows,

*Computation Tim*e

Computation time is computed by dividing the utilizing time by the nodes rate, which is expressed in equation (12) as follows,

$$Computation\,Time = \frac{Utilizing\ Time}{Nodes\ Rate} \tag{12}$$

Energy Efficiency

The energy efficiency of IoT in a 5G network is deliberated by dividing the energy obtained from the output by the initial input energy which is expressed in equation (13) as follows,

$$Energy_{efficiency} = \frac{U_{out}}{U_{in}} \times 100\% \tag{13}$$

Where U_{out} represents the output energy and U_{in} represents the input energy.

4.1.3 Lifespan

The lifespan value is obtained by dividing the sum of nodes' lifespan by the number of nodes which is expressed in equation (14) as follows,

$$Lifespan = \frac{sum\,of\ nodes\,lifespan}{number\,of\ nodes} \tag{14}$$

Lifetime

The lifetime value is obtained by multiplying the lifespan of average nodes with the value of nodes. It is given in equation (15) as follows,

$$LTV = Average\,Nodes\,Lifespan \times Nodes\,Value \tag{15}$$

Scenario 1: Node 100

In this section, data is transmitted through 100 numbers of nodes and the performance is analyzed. **Fig 4-7** shows the Simulation result of IoT Lifespan radius Vs Computation Time, IoT Lifespan radius Vs Energy efficiency, IoT Lifespan radius Vs Lifetime, and IoT Lifespan radius Vs Remaining Nodes for the proposed MOP-hyb-MFRS-IoT-5GN method is compared with the existing method such as MPGA-IoT-5GN, EDTC-GCN-IoT-5GN and CRAN- IoT-5GN respectively.

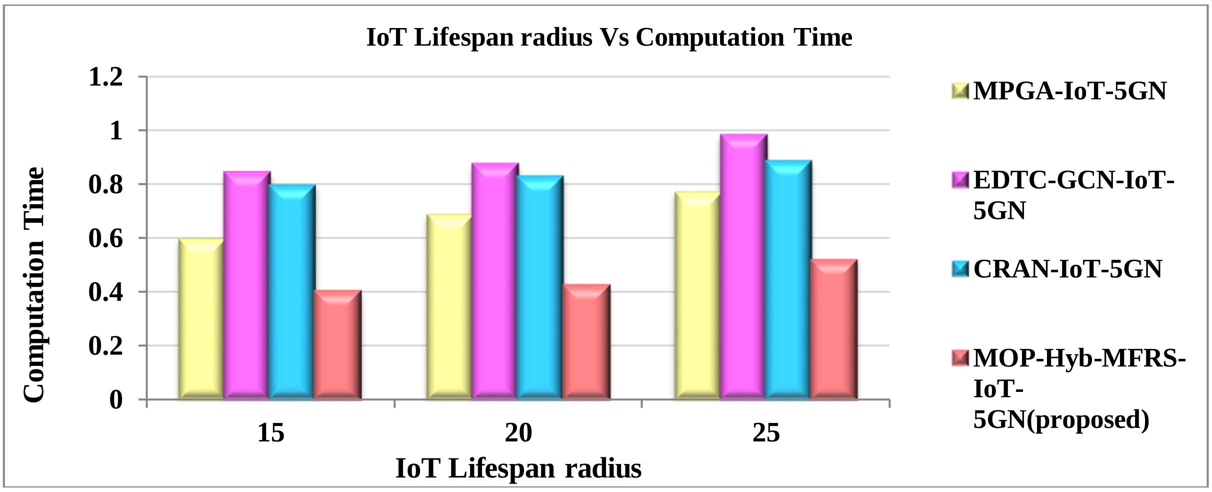

Fig 4. Performance of IoT Lifespan radius Vs Computation Time

Fig 4. shows the performance of IoT Lifespan radius Vs Computation Time. At IoT Lifespan radius 15, the computation time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 12.30%, 16.55%, and 21.56% lower computation time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 20, the computation time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 57.84%, 29.36%, and 39.07% lower computation time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 25, the computation time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 36.85%, 56.30%, and 16.97% lower computation time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

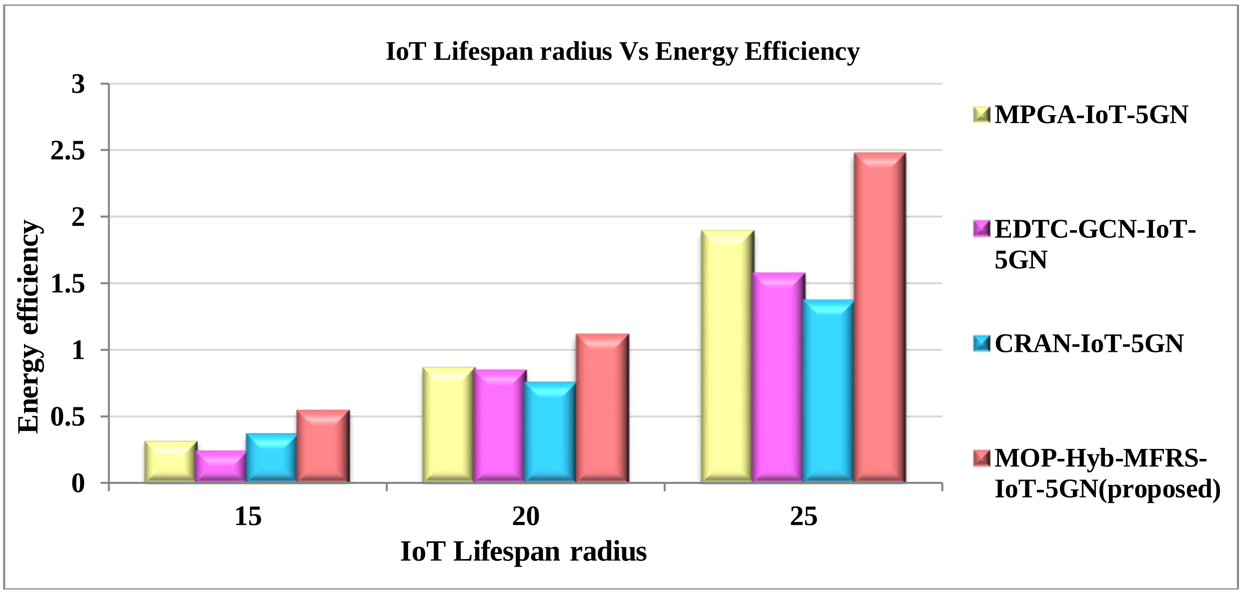

Fig 5. Performance of IoT Lifespan radius Vs Energy Efficiency

Fig 5. shows the performance of IoT Lifespan radius Vs Energy Efficiency. At IoT Lifespan radius 15, the energy efficiency of the proposed MOP-hyb-MFRS-IoT-5GN method provides 18.95%, 36.97%, and 33.12% higher energy efficiency compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 20, the energy efficiency of the proposed MOP-hyb-MFRS-IoT-5GN method provides 57.86%, 66.03%, and 36.11% higher energy efficiency compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 25, the Energy Efficiency of the proposed MOP-hyb-MFRS-IoT-5GN method provides 38.66%, 24.26%, and 22.33% higher energy efficiency compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

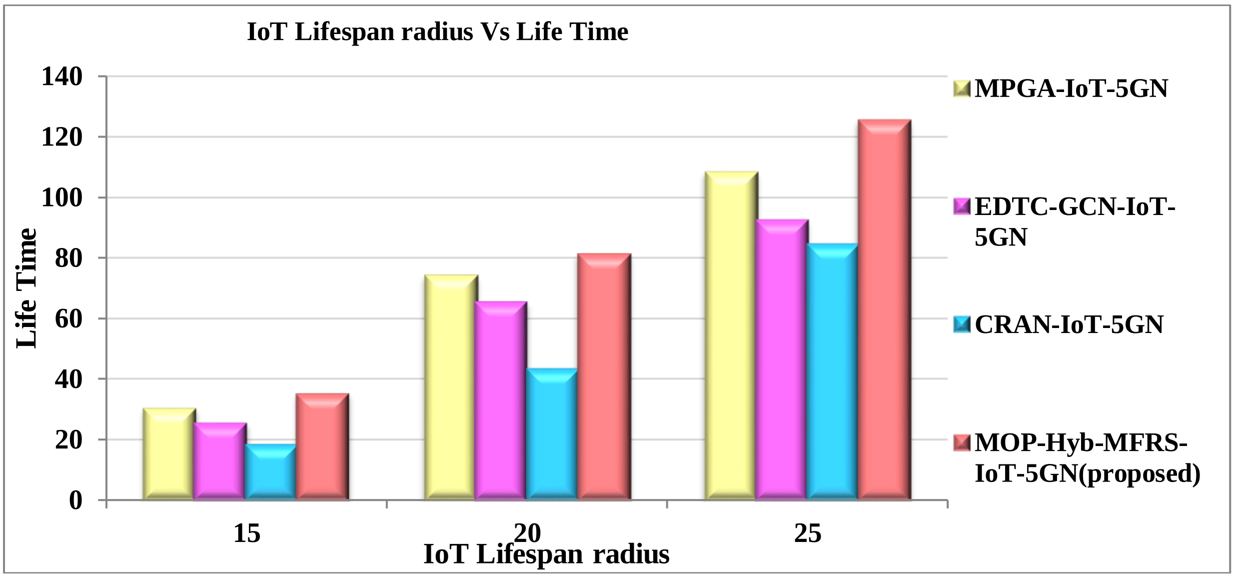

Fig 6. Performance of IoT Lifespan radius Vs Life Time

Fig 6. shows the performance of IoT Lifespan radius Vs Life Time. At IoT Lifespan radius 15, the Life Time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 47.02%, 36.77%, and 32.77% higher Life Time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 20, the Life Time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 27.94%, 62.69%, and 38.35% higher Life Time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 25, the Life Time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 45.96%, 48.06%, and 38.16% higher Life Time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

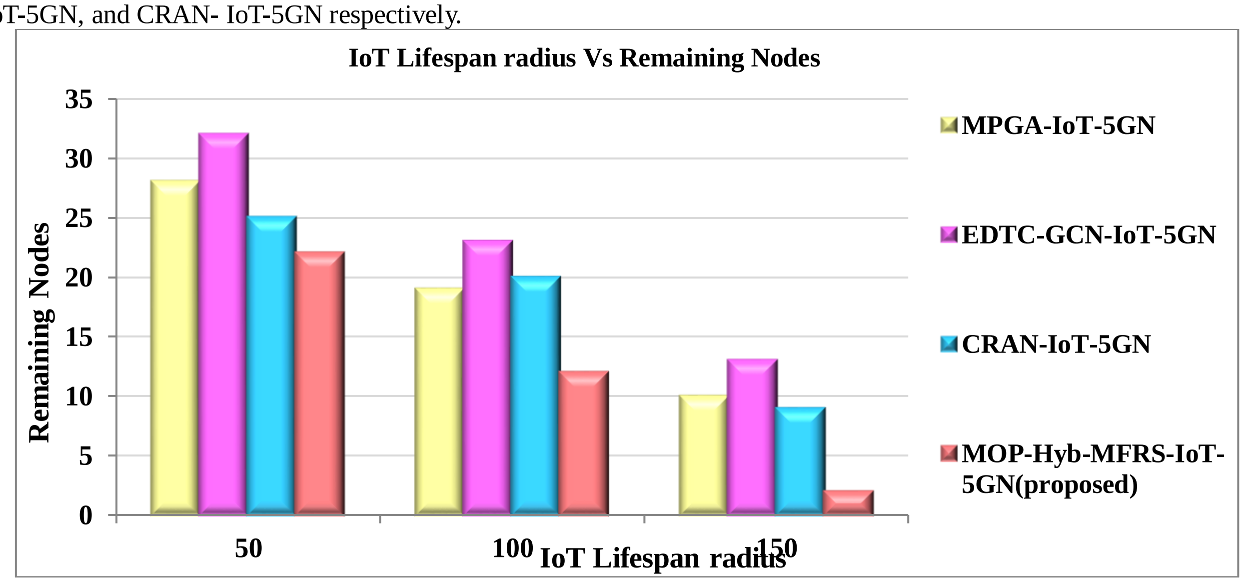

Fig 7. Performance of IoT Lifespan radius Vs Remaining Nodes

Fig 7. shows the performance of the IoT Lifespan radius Vs remaining nodes. At IoT Lifespan radius 50, the remaining nodes of the proposed MOP-hyb-MFRS-IoT-5GN method provide 55.97%, 67.97%, and 58.74% higher remaining nodes compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 100, the remaining nodes of the proposed MOP-hyb-MFRS-IoT-5GN method provide 58.07%, 47.99%, and 54.18% higher remaining nodes compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 150, the remaining nodes of the proposed MOP-hyb-MFRS-IoT-5GN method provide 17.23%, 37.64%, and 19.52% higher remaining nodes compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

Scenario 2: Node 150

In this section, data is transmitted through 150 numbers of nodes and the performance is analyzed. **Fig 8-11** shows the Simulation result of IoT Lifespan radius Vs Computation Time, IoT Lifespan radius Vs Energy efficiency, IoT Lifespan radius Vs Lifetime, and IoT Lifespan radius Vs Remaining Nodes for the proposed MOP-hyb-MFRS-IoT-5GN method is compared with the existing method such as MPGA-IoT-5GN, EDTC-GCN-IoT-5GN and CRAN- IoT-5GN respectively.

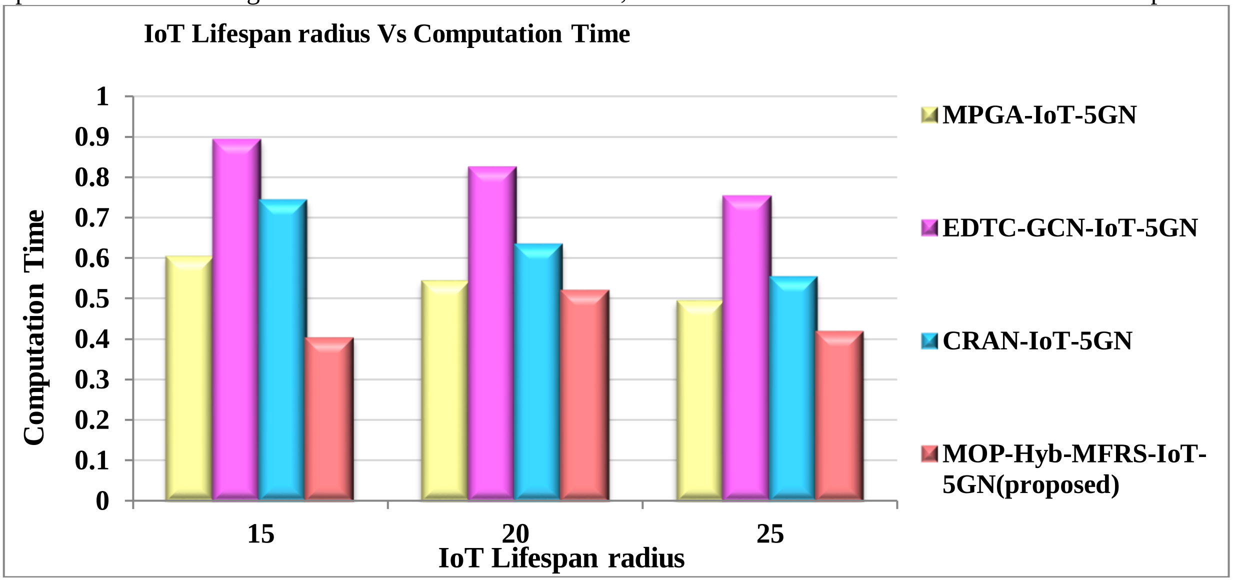

Fig 8. Performance of IoT Lifespan radius Vs Computation Time

Fig 8 shows the performance of IoT Lifespan radius Vs Computation Time. At IoT Lifespan radius 15, the computation time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 23.17%, 62.15%, and 13.55% lower computation time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 20, the computation time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 59.94%, 29.63%, and 67.85% lower computation time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 25, the computation time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 56.97%, 84.97%, and 63.97% lower computation time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

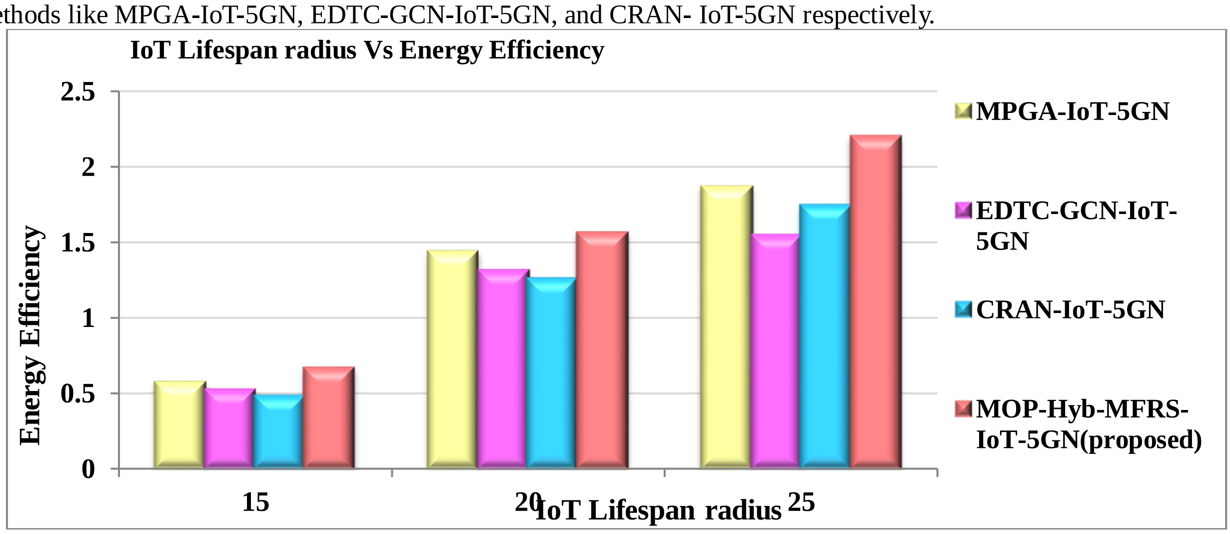

Fig 9. Performance of IoT Lifespan radius Vs Energy Efficiency

Fig 9. shows the performance of IoT Lifespan radius Vs Energy Efficiency. At IoT Lifespan radius 15, the Energy Efficiency of the proposed MOP-hyb-MFRS-IoT-5GN method provides 59.07%, 69.70%, and 48.97% higher Energy Efficiency compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 20, the Energy Efficiency of the proposed MOP-hyb-MFRS-IoT-5GN method provides 37.15%, 43.69%, and 35.71% higher Energy Efficiency compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 25, the Energy Efficiency of the proposed MOP-hyb-MFRS-IoT-5GN systemdelivers36.11%, 29.66%, and 41.31% greater Energy Efficiency likenedto existing like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

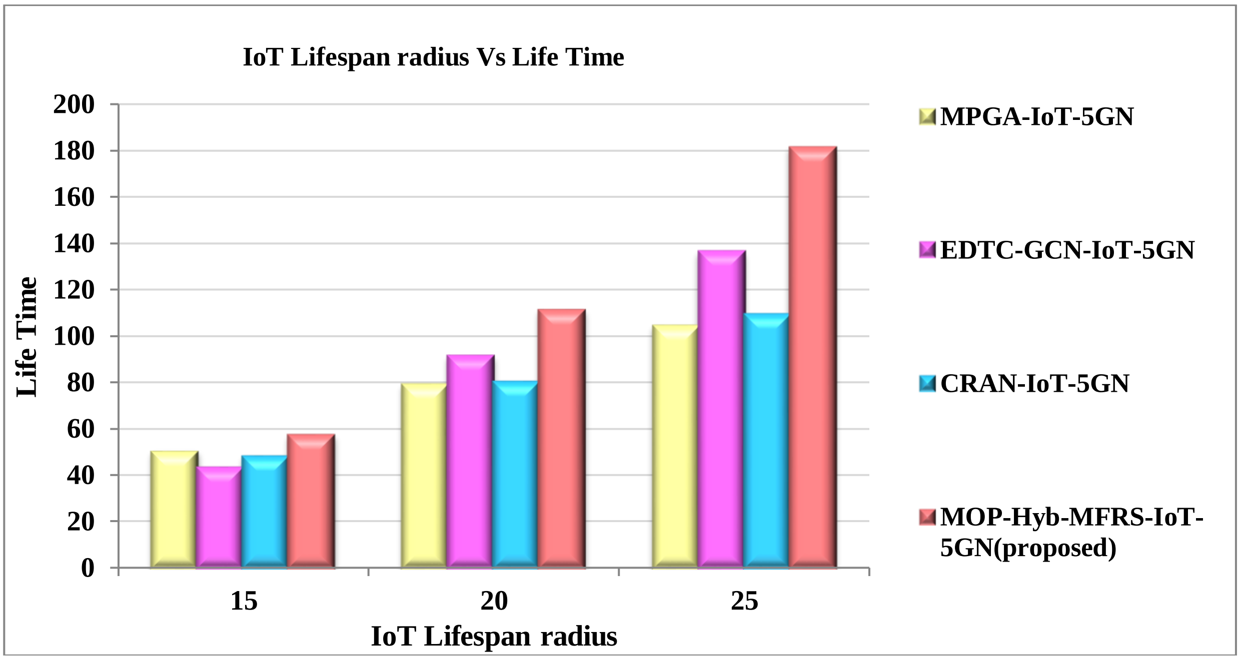

Fig 10. Performance of IoT Lifespan radius Vs Life Time

Fig 10. shows the performance of IoT Lifespan radius Vs Life Time. At IoT Lifespan radius 15, the Life Time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 37.19%, 41.19%, and 16.29% higher Life Time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 20, the Life Time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 71.26%, 38.15%, and 34.69% higher Life Time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 25, the Life Time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 57.97%, 44.59%, and 58.75% higher Life Time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

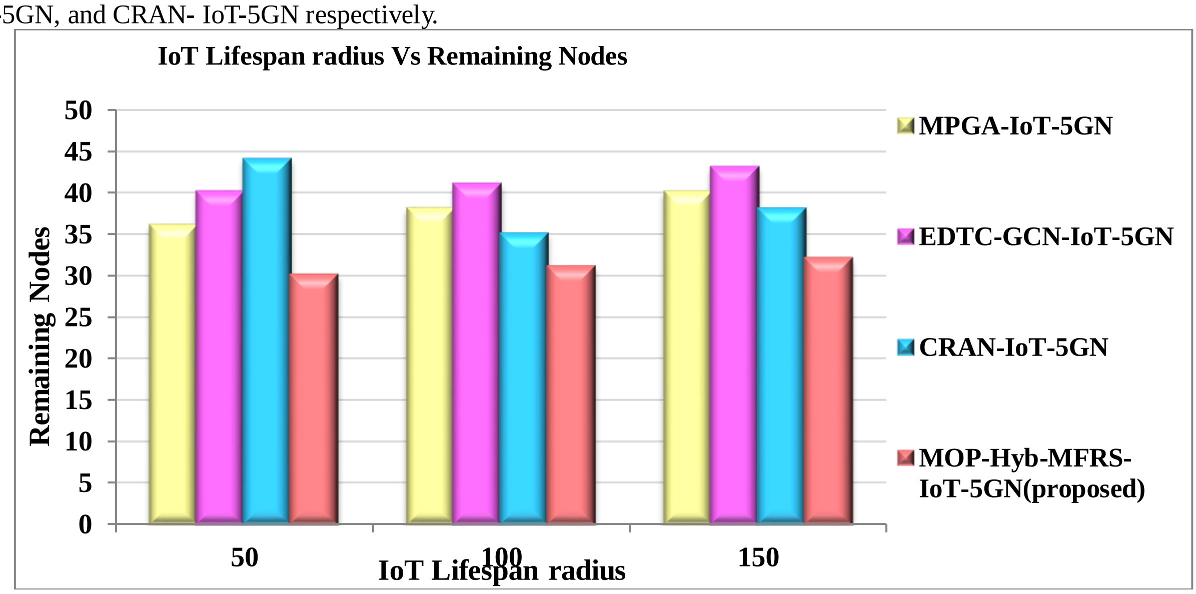

Fig 11. Performance of IoT Lifespan radius Vs Remaining Nodes

Fig 11 shows the performance of the IoT Lifespan radius Vs remaining nodes. At IoT Lifespan radius 50, the remaining nodes of the proposed MOP-hyb-MFRS-IoT-5GN method provide 58.96%, 74.85%, and 49.07% higher remaining nodes compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 100, the remaining nodes of the proposed MOP-hyb-MFRS-IoT-5GN method provide 64.95%, 51.96%, and 48.96% higher remaining nodes compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 150, the remaining nodes of the proposed MOP-hyb-MFRS-IoT-5GN method provide 59.66%, 61.56 and 18.51% higher remaining nodes compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

Scenario 3: Node 200

In this section, data is transmitted through 200 numbers of nodes and the performance is analyzed. Figure 12-15 shows the Simulation result of IoT Lifespan radius Vs Computation Time, IoT Lifespan radius Vs Energy efficiency, IoT Lifespan radius Vs Lifetime, and IoT Lifespan radius Vs Remaining Nodes for the proposed MOP-hyb-MFRS-IoT-5GN method is compared with the existing method such as MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

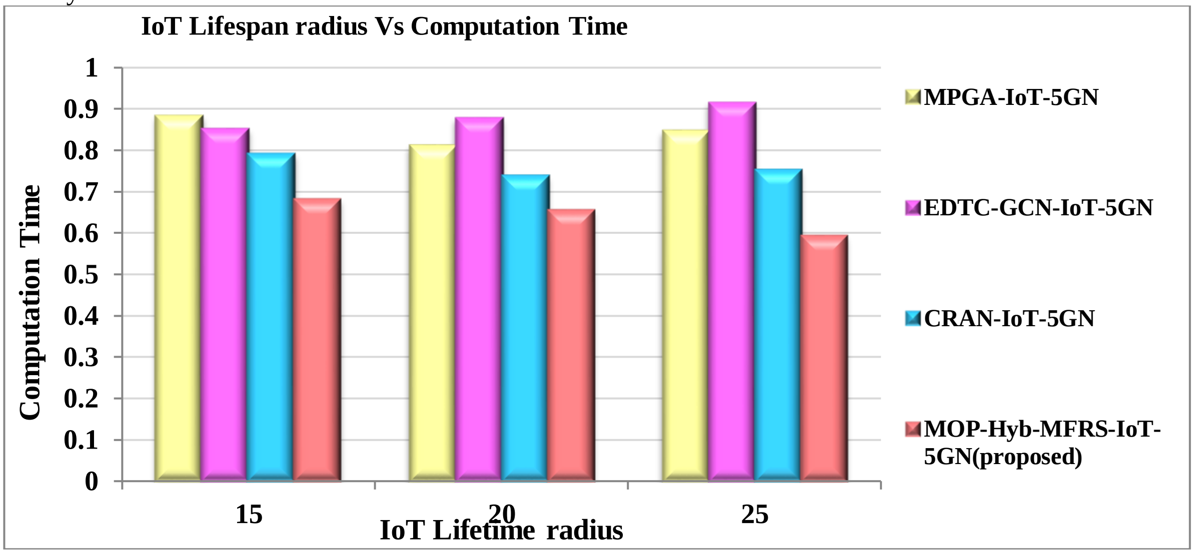

Fig 12. Performance of IoT Lifespan radius Vs Computation Time

Fig 12. shows the performance of IoT Lifespan radius Vs Computation Time. At IoT Lifespan radius 15, the computation time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 45.33%, 36.52%, and 44.23% lower computation time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 20, the computation time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 56.86%, 43.97%, and 47.97% lower computation time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 25, the computation time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 56.86%, 43.97%, and 47.97% lower computation time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

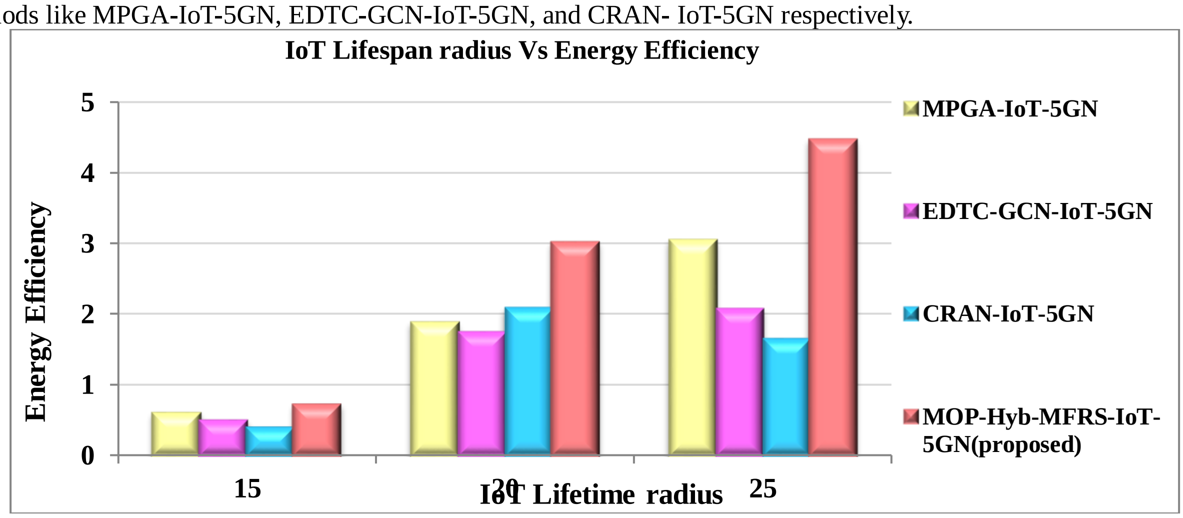

Fig 13. Performance of IoT Lifespan radius Vs Energy Efficiency

Fig 13 shows the performance of IoT Lifespan radius Vs Energy Efficiency. At IoT Lifespan radius 15, the Energy Efficiency of the proposed MOP-hyb-MFRS-IoT-5GN method provides 65.96%, 57.96%, and 57.97% higher Energy Efficiency compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 20, the Energy Efficiency of the proposed MOP-hyb-MFRS-IoT-5GN method provides 59.61%, 32.66%, and 47.52% higher Energy Efficiency compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 25, the Energy Efficiency of the proposed MOP-hyb-MFRS-IoT-5GN method provides 39.16%, 23.51%, and 37.25% higher Energy Efficiency compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

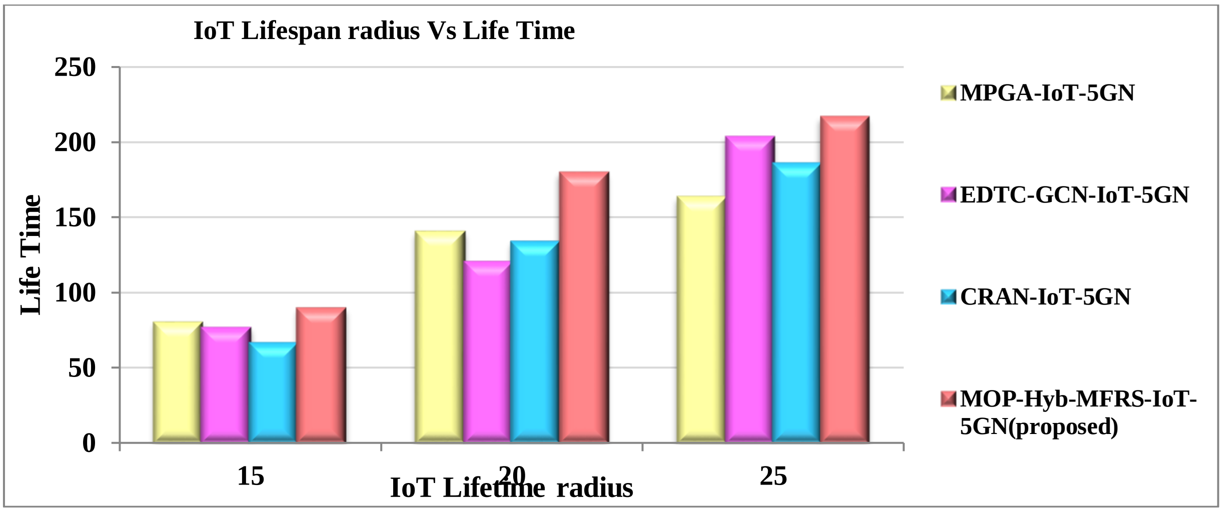

Fig 14. Performance of IoT Lifespan radius Vs Life Time

Fig14. shows the performance of IoT Lifespan radius Vs Life Time. At IoT Lifespan radius 15, the Life Time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 47.96%, 29.97%, and 44.96% higher Life Time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 20, the Life Time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 38.96%, 57.80%, and 41.97%higher Life Time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 25, the Life Time of the proposed MOP-hyb-MFRS-IoT-5GN method provides 37.76%, 39.97%, and 43.75%higher Life Time compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

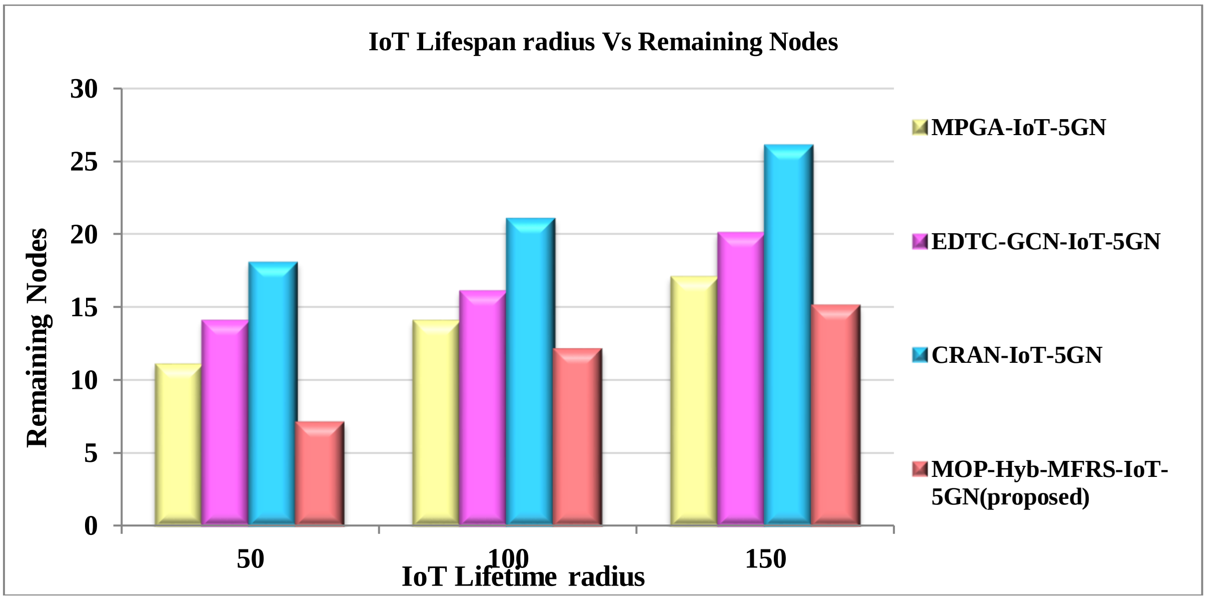

Fig 15. Performance of IoT Lifespan radius Vs Remaining Nodes

Fig 15 shows the performance of the IoT Lifespan radius Vs remaining nodes. At IoT Lifespan radius 15, the remaining nodes of the proposed MOP-hyb-MFRS-IoT-5GN method provide 38.86%, 29.97%, and 47.94%higher remaining nodes compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 20, the remaining nodes of the proposed MOP-hyb-MFRS-IoT-5GN method provide 38.97%, 26.08%, and 55.97%higher remaining nodes compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively. At IoT Lifespan radius 25, the remaining nodes of the proposed MOP-hyb-MFRS-IoT-5GN method provide 43.58%, 38.97%, and 38.97% higher remaining nodes compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and CRAN- IoT-5GN respectively.

V. CONCLUSION

In this manuscript, MOP-Hyb-MFRS using Hadoop is successfully implemented for calculating optimal configuration sequence for IoTs using massive nodes and extending IoT lifespan is successfully implemented.The simulation process is executed in the NS2 platform. The proposed MOP-Hyb-MFRS-IoT-5GNattains high lifespan95.78%, 99.32%, and 91.13%, and High energy efficiency of 88.34%, 90.34%, and 89.72% compared with the existing methods like MPGA-IoT-5GN, EDTC-GCN-IoT-5GN, and LiMCA- IoT-5GN respectively.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Ethics Approval and Consent to Participate

The research has consent for Ethical Approval and Consent to participate.

Competing Interests

There are no competing interests.

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