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Implementation and Performance Comparison of Novel Optimization Approaches to Counter Starvation in Wireless Networks

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Abstract: Data packets in Wireless Mesh Networks (WMNs) are routed across several nodes in a multi-hop fashion. The Quality of Service (QoS), seamless connectivity, reliability, and scalability of Wireless Mesh Networks are all significantly impacted by routing approaches. Routing protocols should enforce the fair utilization of resources i.e. bandwidth or channel among network nodes irrespective of their spatial location from the Gateway. The two-hop or multi-hop nodes in wireless mesh networks experience resource starvation due to the functioning of the MAC protocol and TCP/TP networking protocol. The Starvation issue has a significant impact on the QoS requirements of wireless mesh networks. It is known that using appropriate scheduling techniques in network planning substantially minimizes starvation. To reduce the starving of resources to the multi-hop network nodes, novel optimized routing algorithms have been proposed and implemented in this work. To address the starvation, a GA-based cross-layer optimized scheduling method that operates at the MAC and Network layers is implemented. A hybrid approach that combines the features of the Genetic Algorithm (GA) and Gravitational Search Algorithm (GSA) is also implemented to solve the local minimum problem in GA. Results show that the suggested optimization methods greatly improve the fairness performance of wireless mesh networks.

Index Terms: Wireless Mesh Networks (WMNs), Quality of Service (QoS), Resource Management, Starvation, Cross-layer Optimization, Genetic Algorithm, Gravitational Search Algorithm.

1. Introduction

Wireless mesh networks (WMNs) constitute a packet-switched architecture comprising mobile nodes, access points, and network gateways [1]. These networks leverage wireless nodes and a backbone to extend high-speed Internet access to 'last mile' users, showcasing fault-tolerant, self-organizing, self-healing, and self-optimizing capabilities for mobile Internet users. The rapid deployment, cost-effectiveness, and low overhead costs of WMN technology make it a potent solution in wireless environments. However, persistent challenges such as fairness and resource starvation issues detract from the overall benefits of WMNs. The efficient implementation of these networks is further complicated by user demands for Quality of Service (QoS) necessitating robust resource management.

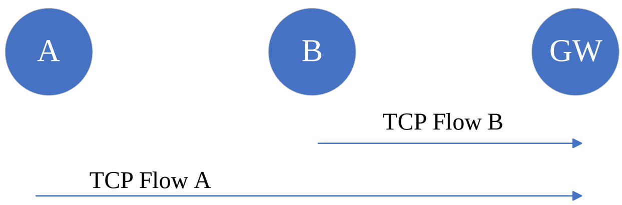
Routing within WMNs poses a multi-objective optimization challenge, particularly in meeting QoS requirements such as packet delivery ratio, throughput, end-to-end delay, and jitter [2,3]. To address QoS routing concerns, the adoption of an efficient metaheuristic method with accelerated convergence becomes imperative. Additionally, in tackling fairness and starvation problems, solutions implemented at the Medium Access Control (MAC) layer play a pivotal role in enhancing overall network performance and alleviating resource scarcity [4].

Ghaleb et al. [5] presented a noteworthy advancement in the field, offering a fair-oriented semichaotic genetic algorithm-based channel assignment technique to mitigate the node starvation problem in wireless mesh networks. Potti et al. [6] explored innovative strategies to mitigate starvation, a critical challenge affecting resource allocation and performance in wireless mesh networks. The methodologies outlined in existing literature offer partial relief to the issue of starvation in wireless mesh networks (WMNs) but fall short of enhancing the Quality of Service (QoS) performance crucial for delivering seamless connectivity at accelerated rates to end users. Effective optimization techniques are essential to address starvation concerns and elevate the overall QoS performance of WMNs. Notably, prior research lacks comprehensive strategies for optimizing resource allocation to tackle the starvation problem. This research aims to fill this gap by implementing algorithms and methodologies operating at both the Medium Access Control (MAC) and Network layers to effectively resolve the starvation challenge in Wireless Mesh Networks, validated through the use of the OPNET simulation tool. The key contributions of this study encompass:

- Development of an optimized framework for network planning, featuring an initial Genetic Algorithm-based optimization method. This method enhances throughput and packet delivery ratio (PDR) performances in WMNs by effectively circumventing throughput imbalances among network nodes, thereby mitigating starvation.
- Proposal of a Hybrid Genetic Optimization algorithm incorporating the Gravitational Search Algorithm (GSA). This hybrid approach is designed to counteract the slow convergence of the Genetic Algorithm, ensuring optimal adjustment of the mesh node contention window to further address starvation issues.

2. Protocol Originsof Starvation

Shi et al. [7], Babu et al. [8], Bhargavan et al. [9] and M. Garetto [10] demonstrated the existence of starvation in wireless mesh networks. It was illustrated that the bi-stability caused by CSMA/CA mechanism, the asymmetry induced by transport protocol and the subsequent penalties on transmission are the protocol origins of the starvation. The basic scenario (Fig.1) was considered to describe how MAC mechanisms interact with TCP congestion control mechanisms to cause starvation.

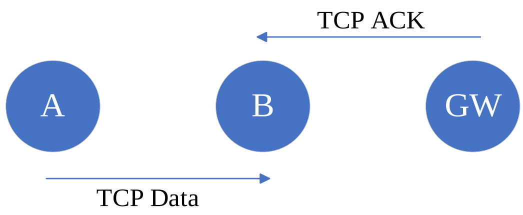


Source: J. Shi et al 2008

Fig.1. A basic scenario in a wireless mesh network

The bi-stability was examined by considering the scenario in which two-hop mesh node A and gateway node GW contend with each other for transmitting TCP DATA and TCP ACK respectively as shown in Fig. 2.

In the above scenario, when the mesh node A (or GW) acquire the channel, it enters a success state in which it is able to transmit multiple packets, while the mesh node GW (or A) enters a fail state in which it is unable to transmit packets. Both nodes A and GW are in the sensing range of node B, so it can contend fairly with the node that is in the success state and interleave its packets. Because of this bi-stability, either (A, B) or (B, GW) wins the channel most of the times.



Source: J. Shi et al 2008

Fig.2. Illustrating the asymmetric bi-stability

It was illustrated that the system spends dramatically different times in the two possible stable states due to TCP congestion control mechanisms. Hence, there is more possibility for the system to spend more time in the stable state in which (B, GW) captures the channel than in the state in which (A, B) captures the channel. This means that the one-hop flow (B, GW) uses the channel most of the time and the two-hop flow (A, B, GW) get starved.

Moreover, it was proved that the asymmetric bi-stable states often incur penalties on the transmitter of the starved node in terms of packet drops, delay and throughput. In this way, the two-hop flows are got starved when they contend with one-hop flows. This unfair utilization of channel resources is called starvation and it severely affects the QoS performance of the wireless mesh networks. The QoS performance of a WMN is determined in terms of packet delivery ratio, throughput, end-to-end delay, jitter, routing load, number of control packets and fairness. Starvation is also identified in broader topologies in which there are two or more branch scenarios consisting of one-hop and two-hop or multi-hop flows.

3. Methodology

Addressing the starvation challenge in Wireless Mesh Networks (WMNs) is achievable through meticulous network planning. This endeavor aims to ensure a fair distribution of network bandwidth among users, thereby enhancing overall network throughput efficiency [11]. To counteract starvation and facilitate careful network planning, optimization methods come into play. This study advocates the use of a dominant, nature-inspired, and evolutionary computing approach known as the Genetic Algorithm (GA) to tackle the multi-constrained Quality of Service (QoS) routing problem.

The Genetic Algorithm proves its effectiveness in network planning by evolving towards optimal solutions across generations, eliminating suboptimal solutions in the process. In the realm of WMNs, various global optimization strategies, such as Ant Colony Optimization (ACO) and Tabu Search (TS), have been proposed for addressing routing and channel allocation issues. Given its suitability for large networks and simplicity, the Genetic Algorithm emerges as an ideal choice for maximizing resource utilization in wireless mesh environments.

This research primarily focuses on a Genetic Algorithm-based optimization strategy tailored to alleviate the starvation issue in WMNs. The proposed approach optimally adjusts the contention window of mesh nodes. To address the slow convergence inherent in genetic algorithms, a hybrid algorithm is introduced, integrating the Genetic Algorithm with the Gravitational Search Algorithm (GSA). This hybridization incorporates GSA's local search functionality into GA, resulting in accelerated convergence.

3.1. Genetic Algorithm

Inspired by Darwin's theory of evolution, Genetic Algorithms (GAs) have revealed a variety of characteristics that are especially useful for optimization, engineering and computer science applications. To produce optimal solutions to search problems, this metaheuristic algorithm is consistently applied. While alternative methods have been suggested based on the notion of evolutionary computation, the literature has received comparatively superior attention to multi-objective optimization with Genetic Algorithm.

Genetic Algorithms (GAs) are evolutionary algorithms implementing the selection process as found in nature. GA begins with an individual initial population, i.e., possible problem solutions with every solution having an associated fitness value indicating its fitness compared to others. GA practices a similar way of evaluation, selection, crossover, mutation and replacement in producing a next generation of individuals, as it happens in nature. This is repeated through many generations during which best features of parents pass on to the offspring; therefore, individuals with improved fitness are finally obtained [12]. In fact, the mechanism of natural selection that follows the rule of survival of the fittest is inspired by GAs. Because of their applicability, ease of use, and global perspective, GAs are used extensively to solve complex real-world optimization issues [13].

Similar to simulated annealing, Genetic algorithms can be used to find near-optimal solutions. Unlike the branch and bound method, these are applicable for planning and optimization of large WMNs as they are faster. The GA process steps are as given below:

i) A random population of ‘n’ chromosomes is generated.
ii) The fitness of each chromosome is evaluated in the population.

iii) A new population is generated as follows:

a. By considering the degree of desirability, few pairs of chromosomes are selected.
b. A crossover operator is applied on selected pairs of chromosomes and a new offspring for each chromosome pair is generated.
c. Calculation of mutation probability for each offspring and changing present genes in offspring based on comparison of their mutation probabilities and the overall mutation probability.

iv) For the next iterations of the algorithm, new population is used.
v) By considering the stop conditions, the process is stopped and the best response is returned.
vi) Going back to step 2 [14].

Basic Model Description

As mentioned in the above section, for a particular problem, GA mechanism works by considering random individual population. Each individual's fitness (quality) in the population is assessed by the fitness function. A standard Genetic Algorithm calls for:

i) A hereditary representation of the domain of the solution (encoding).
ii) A fitness function to determine the domain of the solution.

The basic representation is binary encoding, but it is not favoured for all sorts of problem domains. Hence encoding scheme and fitness function are always problem dependent. The fitness function is well-defined by considering the solution's quality requirement. Initializing the population involves determining the population size and method of initialization. The population size is usually decided based on the problem domain and at times it may be tuned in each iteration in order to achieve better results. Each individual’s fitness is evaluated in every generation. A new iteration of the population is formed by selecting individuals based on their fitness for reproduction and adding their offspring to the population. By this repetitive procedure, the average fitness value of the population will increase.

Selection can either be performed among all the individuals of the population or with a random sample as the former method is time consuming. Many methods are available on selecting best chromosomes, for instance, Roulette wheel selection, Boltzmann selection, Stochastic universal sampling, Tournament selection, Rank selection, steady state selection, truncation selection, elitist selection and some others. Different types such as a crossover, two-point crossover, multi-point crossover and personalized crossover can be used as a cross-over or recombination procedure. Since the crossover operator may have a major effect on the outcome of a search, this is typically used based on the optimal crossover likelihood value selected.

The crossover exchange is conducted at selected crossover sites with single bits or group of bits of two individuals. It can be used potentially to L - 1 different crossover sites (where L is the length of the individuals). The single-point crossover is favoured in most of the issues.Fig. 3 reveals the single-point crossover process with an instance.

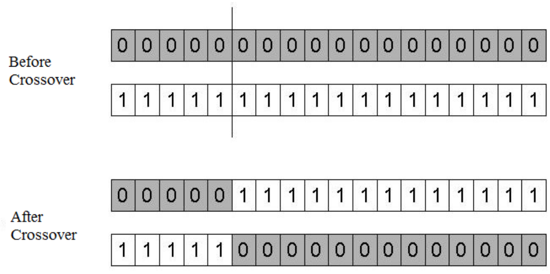


Fig.3. Single-point crossover operation

Two individuals are lined up in a single point crossover and one position is randomly selected as a crossover site for their strings. At this crossover site two parents will be separated and a new descendant (children) will be made up of exchanges of tails. For the creation of new genetic structures unrelated to earlier genetic structures, mutation randomly flips one or more bits from individuals in a population. The mutation prevents the local minima of the algorithm. The latest genetics are connected to other parts of the huge search space. Fig. 4 demonstrates the mutation process.

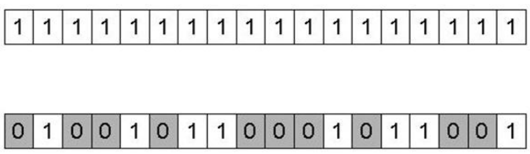


Fig.4. Mutation process

The population is skewed towards convergence by the GA parameters of crossover rate or probability, mutation probability, and population size. However, it should be kept in mind that a value that is either too low or too high will surely cause the solution package to differ. When the population meets the minimum requirement or the maximum number of completed iterations, the iterative genetic algorithm process is terminated.

3.2. Starvation Mitigation using Genetic Optimization

Traditional algorithms designed for quality-of-service routing in Wireless Mesh Networks (WMN) fall short in providing a global solution due to the NP-hard nature of the problem. This study introduces a metaheuristic optimization algorithm, namely Genetic Optimization, to address the starvation problem in unicast routing within WMNs. Leveraging functions from both the network and MAC layers, this cross-layer technique aims to prevent starvation in multi-hop nodes by determining optimal Contention Window (CW) values for each node based on network layer Quality of Service (QoS) parameters and the available channel.

Within the proposed framework, factors such as the hop distance from the gateway, packet loss rate, and network layer delay play a crucial role in determining the contention window size for each node. The method aims to identify the best routes from the source to the gateway at the network layer and determine optimal contention window sizes for individual nodes at the medium access control (MAC) layer, thereby mitigating starvation in two-hop or multi-hop nodes.

In the implementation of this method, a random set of routes is selected from the available paths between the source and the gateway. Subsequently, each node in the chosen set of routes is assigned a random minimum contention window. The network is then evaluated iteratively using a given fitness function to assess its performance and optimize routing parameters, ultimately alleviating the starvation issue in WMNs.

This process of fitness evaluation optimizes the contention window for multi-hop nodes and one-hop nodes to minimize the packet loss rate. The GA-optimized contention window of each node is used in the DCF of IEEE 802.11 to schedule channel access. The fitness function defined for this optimization is given in Eq.

$$f(t) = \frac{D_i}{D_{\max} e^{-(cache_i - cache_{\max})}}$$

Where D_i = End-to-end delay in i^{th} iteration
D_{max} = Maximum end-to-end delay = 500ms
$cache_i$= Cache utilized in i^{th} iteration
$cache_{max}$ = maximum size of cache = 512k bytes

The mapping of wireless mesh network environment with genetic environment and various genetic parameters used in this method are given in Table 1. A four-bit binary code is used to encode the hop distance of the nodes from the gateway.

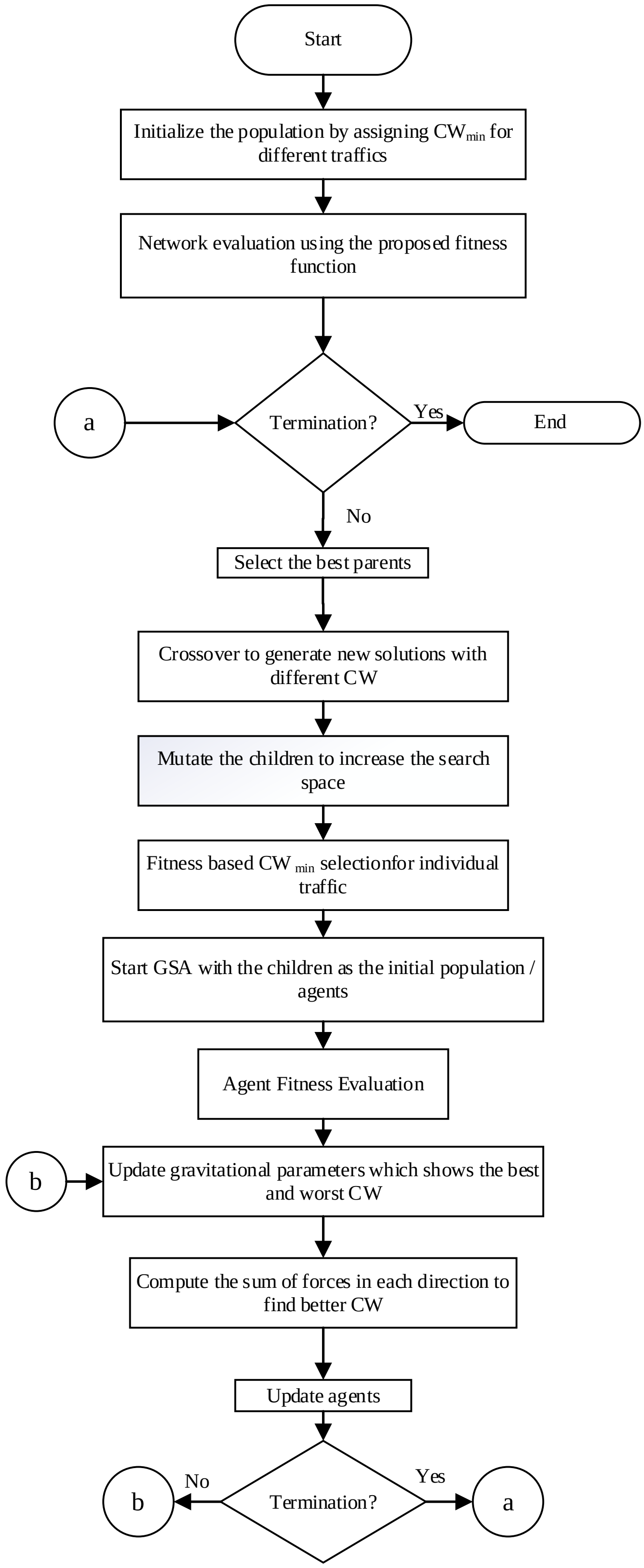
3.3. Gravitational Search Algorithm (GSA)

The Gravitational Search Algorithm (GSA) operates as a heuristic optimization method grounded in the principles of gravity and motion laws [15]. Its application aims to augment the exploration and exploitation capabilities inherent in any population-based algorithm. GSA employs a group of search agents represented as objects; each undergoing interaction influenced by gravity forces. The outcomes are determined based on the mass associated with each object.The gravitational force arises from a global movement, compelling these objects to converge due to the influence of heavier masses. This characteristic proves beneficial when seeking optimal solutions, particularly in scenarios where the motion of heavier masses is deliberate and gradual. Potti et al. [16] and [17] have meticulously elucidated the comprehensive mathematical formulation of the Gravitational Search Algorithm, providing insights into its mechanics and the derivation of optimal solutions.

3.4. Hybrid GA Optimization

The strategy for mitigating starvation, termed Genetic Optimization, is elaborated in Sections 3.1 and 3.2. While the Gravitational Search Algorithm (GSA) exhibits superior convergence compared to the Genetic Algorithm, it falls short in global search capability. This study addresses this limitation by hybridizing the Gravitational Search Algorithm with the Genetic Optimization algorithm, aiming to bolster local search capabilities and enhance overall convergence. The resulting hybrid optimization algorithm functions on both the network layer and the MAC layer, leveraging their respective functionalities. In this model, the determination of the contention window size for each node, as outlined in Section 3.2, plays a crucial role. Moreover, the proposed optimization is seamlessly integrated with the AODV routing protocol.

Within this optimization framework, the input parameters are characterized by hop distance, packet loss rate, and end-to-end delay. The desired output is a collection of optimal routes from the source to the gateway, accompanied by the corresponding minimum contention window (CWmin) values for individual nodes. The optimization process focuses on minimizing packet loss rates and achieving the most favourable solutions. The proposed hybrid optimization's flow chart, depicted in Fig. 5, outlines the sequential steps involved.



Termination Condition for GA & GSA: End of all iterations or fitness ≤ 0.001

Fig.5. Hybrid GA optimization model

Table 1. Mapping of WMN environment with GA and GA parameters

GA Terminology	WMN Environment
Population	Set of arbitrary viable paths
Individual/Candidate solution	Source to gateway Path
Chromosome	Node count, Data Loss Rate, Delay and path to the gateway from source end-to-end delay.
Gene	Bits representing node count, data loss rate and delay
Fitness Function	Based on the end-to-end delay and cache size
Encoding scheme	Real-valued continuous variables in the IEEE 754 floating-point format are used to represent packet loss rate and end-to-end delay
Formation of initial population	Random
Population size	10
Selection method	Roulette wheel
Crossover type	Single-point crossover
Crossover probability	0.5
Mutation rate	0.75
Number of generations (No. of iterations)	250

Table 2. Mapping of WMN environment with GSA and GSA parameters

GSA Terminology	WMN Environment
Population	Set of arbitrary viable paths obtained from GA
Individual/Candidate solution	Path from source to gateway
Gravitational constant (G_0)	20
Maximum number of iterations	250
Constant α	5
Constant ε	0.01

In this hybrid optimization approach, the population generated through Genetic Algorithm (GA) Optimization serves as the initial population for the subsequent application of the Gravitational Search Algorithm (GSA). The effectiveness of GSA is assessed based on Quality of Service (QoS) requirements, emphasizing fitness evaluation. The mapping of the Wireless Mesh Network (WMN) environment with GSA, along with the associated GSA parameters, is detailed in Table 2 for comprehensive understanding and application.

4. Simulation Results and Performance Analysis

With the OPNET simulation platform, the proposed optimization methods have been simulated. Table 3 presents the simulation environment considered for this work. We have carried out simulations with various nodes. To simulate network behavior in a multi-hop environment, multimedia TCP flows are employed. The suggested strategy incorporates the AODV routing protocol.

Table 3. Simulation set up for performance evaluation

Area	4 X 4 km
Traffic type	Multimedia with random TCP flows
Size of each packet	512 Bytes
MAC Protocol	802.11
Routing Protocol	AODV with proposed GA-GSA Optimization
Transmission range/node	250 m
Antenna type	Omni directional
Channel Bandwidth	2 Mbps
Node Mobility	20 Kmph
Simulation Time	180 sec

The proposed method's efficacy in enhancing throughput across various hops and fairness index is demonstrated through a comprehensive validation against two benchmark methods: the Fair Binary Exponential Back-off Algorithm (FBEB) and the IEEE 802.11 method. Notably, the FBEB algorithm operates by indirectly estimating network traffic and subsequently adjusting the contention window of nodes. However, a noteworthy limitation arises from its inability to promptly reset the contention window of a node following a successful transmission; instead, it adheres to a predetermined time delay.

In instances of packet collisions, the FBEB algorithm adopts a strategy of doubling the contention window of a node, necessitating a reinitiation of channel access after the fixed waiting period. This approach, unfortunately, introduces challenges for other nodes grappling with collision-related issues, thereby resulting in a reduction in overall network throughput.In stark contrast, the Hybrid Genetic Algorithm (GA) Optimization presents a marked improvement in throughput. This enhancement is attributed to its dynamic adjustment of contention windows for nodes, taking into account Quality of Service (QoS) parameters. Unlike the FBEB algorithm, the Hybrid GA Optimization exhibits adaptability by altering contention windows in real-time, leading to a substantial boost in network throughput.

In these simulations, in terms of average packet delivery ratio (PDR), average end-to-end delay, average number of hops to sink, number of control packets (Overhead) and normalized routing load, the performances of the proposed GA Optimization (GAO) and Hybrid GA Optimization (HGAO) are analyzed. The results obtained for GAO and HGAO are compared with 802.11, DWRR [18] and FBEB [19] for nodes between 50 and 300. Fig. 6 compares the results obtained for average packet delivery ratio with the five approaches described. HGAO generates 14 to 33.56 percent improvement in the average delivery ratio of packets over the 802.11 method, 12.76 to 32.79 percent improvement in the average delivery ratio of packets over the FBEB approach, 5.58 to 23.13 percent improvement in the average delivery ratio of packets over the DWRR method and 1 to 4.11 percent improvement in the average delivery ratio of packets over the GAO method.

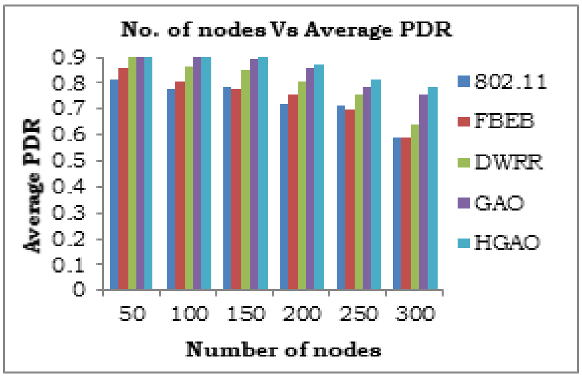


Fig.6. Average PDR performance of hybrid GA optimization

Irrespective of network size, HGAO improves the average packet delivery ratio in all the simulation scenarios. This clearly indicates the effective sharing of the channel resources among all the network nodes. As Fig. 7 illustrates, HGAO outperforms DWRR, FBEB and 802.11 approaches in reducing the average end-to-end delay. Though, HGAO shows a little improvement in delay performance compared to GAO. As depicted, HGAO results in 21.54 to 86.37 percent reduced delay than 802.11 method, 21.11 to 86.2 percent reduced delay than FBEB approach, 15.59 to 85.42 percent reduced delay than DWRR and 0.54 to 2 percent reduced delay than GAO method.

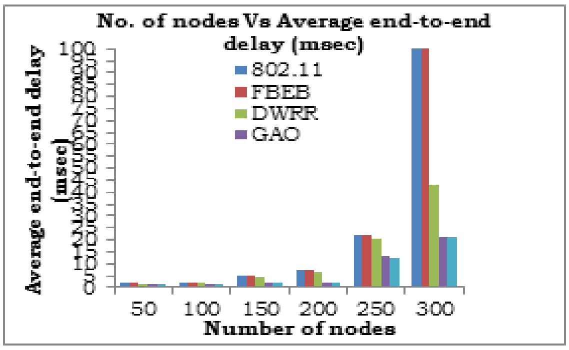


Fig.7. Average end-to-end delay performance of hybrid GA optimization

The performance of HGAO in usage of average number of hops to sink for data transmission is similar to that of GAO as shown in Fig. 8. HGAO uses a greater number of hops for data transmission when the network size falls between 50 and 100 nodes compared to 802.11, FBEB and DWRR approaches. When the network is becoming large from 100 nodes, HGAO uses less average number of hops to sink because of availability of more alternative routes. A little improvement of 0.22 to 2 percent is identified in usage of number of hops to sink with HGAO when compared with GAO.

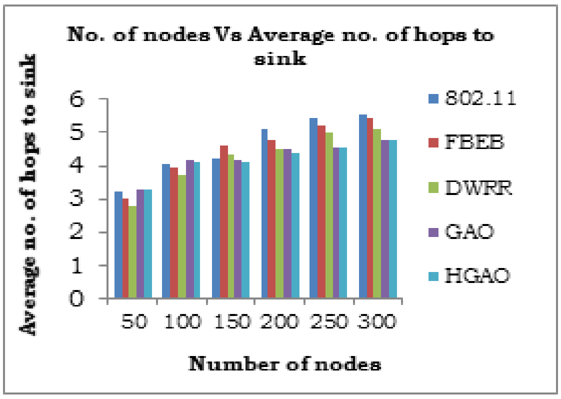


Fig.8. Average number of hops to sink comparison

Fig. 9 compares the simulation results obtained for average jitter with HGAO, GAO, DWRR, FBEB and 802.11 approaches. At the end of each simulation the jitter values are noted and average is calculated. The graph illustrates that the average jitter is reduced while using HGAO when compared to 802.11, FBEB and DWRR methods. An additional 1 percent reduction in average jitter is achieved with HGAO compared to GAO.HGAO results in 30.57 percent reduced average jitter when compared with 802.11, 31.44 percent reduced average jitter when compared with FBEB and 27.23 percent reduced average jitter when compared with DWRR. The number of control packets (Overhead) computed under varying number of nodes is shown in Fig. 10.

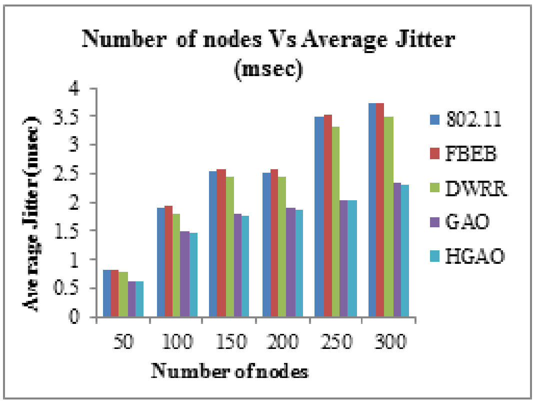


Fig.9. Average jitter performance of hybrid GA optimization

The proposed HGAO used 5.23 percent less control packets compared to 802.11, 20 percent less control packets compared to FBEB, and 15.31 percent less control packets compared to DWRR and 5 percent less control packets compared to GAO. The additional reduction in control packets results from faster convergence achieved with GSA.

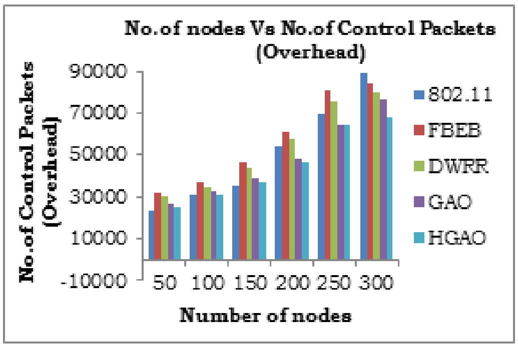


Fig.10. Number of control packets (overhead) comparison for hybrid GA optimization

Fig. 11 presents the variation of normalized routing load for Hybrid GAO, GA Optimization, 802.11 and FBEB approaches. It is identified that there is 2.78 to 36.36 percent reduced normalized routing load for HGAO when compared with 802.11. Moreover, HGAO presents 17.39 to 35.71 percent reduced normalized routing load when comparedto DWRR and 5.7 percent average reduced normalized routing load when compared with GAO. Importantly, HGAO results in improvement in reducing the routing load irrespective of network size.

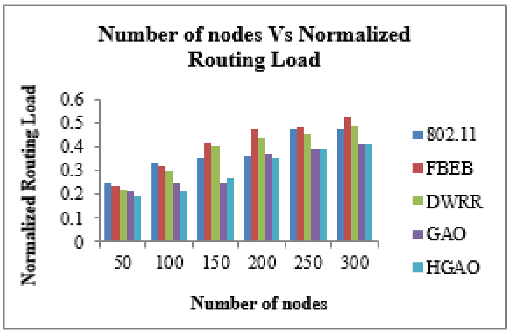


Fig.11. Normalized routing load comparison for hybrid GA optimization

5. Conclusions

In this work, the application of GAO and HGAO optimization techniques took center stage in addressing the critical issue of starvation within Wireless Mesh Networks. The simulations were conducted across dynamic node ranges spanning from 50 to 300, and rigorous benchmarking against DWRR, 802.11, and FBEB methods was executed. The comparative analysis yielded compelling results, highlighting that the Hybrid Genetic Optimization (HGAO) stood out significantly. HGAO showcased notable improvements across various metrics, including enhanced packet delivery ratio, minimized average end-to-end delay, reduced sink nodes, jitter, control packet count (Overhead), and normalized routing load when juxtaposed against conventional 802.11 and FBEB approaches. The superior performance of HGA Optimization was evident, demonstrating reduced overhead and normalized routing load, all while maintaining favorable end-to-end delay, packet delivery ratio, and jitter metrics, surpassing the achievements of GA Optimization.

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