Performance Measurement of Small Cell Power Management Mechanism in 5G Cellular Networks using Firefly Algorithm

Original Scientific Paper

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Abstract – *In cellular networks, with the increase in demand, designing a base station (BS) with less energy consumption remains a challenge for researchers. Also, in a heterogeneous network that is dense in nature, the distribution of numerous small BS has become a challenging issue in terms of expanding the cost of energy. In this paper, we investigate an optimized nature-based cluster sleep technique for reducing the power consumption in the BS as well as the interference in the network. The small BS are grouped along with the interference, which is assumed to be the cluster, which is quite large, where the fire fly (FF) algorithm is applied to frame the sleep technique for the small BS. These FF algorithms, which are based on fire fly attractiveness behavior, improve connectivity among the base stations in an energy-efficient way. The outcomes reveal that the projected sleep technique with the FF algorithm reduces the power consumed by the BS and also gives satisfactory performance for mobile users. The results were compared with the other techniques, such as BS conventional sleep mode and BS sleep mode with LEACH. The proposed method outperformed the other techniques.*

Keywords: *Firefly algorithm, Base station, sleeps technique, power consumption, and heterogeneous network*

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1. INTRODUCTION

In cellular networks, reducing energy consumption is a challenging topic of interest and is beneficial for both telecommunication operators and the global environment [1]. Also, in recent years, there has been a tremendous increase in the usage of mobile data, which is predominantly determined by smart phones, which offer user-friendly internet access and a variety of multimedia applications. On the whole, information and communication technology (ICT) is accountable for about 2% of CO2 emissions globally, and it will reach 4% in 2021 [1]. The conventional BSs have not been able to offer quality of service (QOS) to mobile users. According to the 2012 census, there were nearly 5.8 million conventional BSs worldwide, and it was expected to be more than 10 million in 2020 [2]. As of now, the global number of small BS (SBS) has now exceeded the conventional numbers. Thus, the increase in energy demand over the past few years has given way to green communication in cellular networks. And it is a well-known fact that the cellular network BS is the one that consumes two-thirds of the energy consumed by the whole radio access network. Consequently, reducing the energy utilized by the BS has become the main topic of research.

Energy-efficient BS can be achieved from many perspectives, like using energy-efficient power amplifiers, making use of renewable resources, and also deploying relays and small BSs. Cell zooming can also be used to reduce the energy consumption of BS. In practice, cell zooming reduces the number of active BS when there is low traffic. At the point when few BSs are switched off, the remaining active BSs tend to zoom out for an uninterrupted quality of service (QOS). It is necessary to control the transmission power of the cellular network, as 50–60% of total energy is consumed by the processing circuit and cooling system when the BS is in a working state [3]. According to the data set presented in [4], the data traffic during the day is much larger than the data traffic at night. And also, it slightly varies from normal work days to the end of the week. As discussed, earlier SBS can be maintained and deployed easily as compared to conventional ones, which also require low transmission power. Of the advantages stated above, these SBS form a heterogeneous network (HNET) along with the macro-BS (MBS). Basically, the main idea behind SBS is to reduce the heavy load encountered by MBS for a better QOS. But on the other side, due to the large number of SBS, the newly formed HNET experienced severe interference in terms of both cross-tier interference and co-tier interference [5].

The source of intrusion is the variance in power among the nodes due to the deployment of cells, which are not planned beforehand as they can be switched on and off at any time or moved anywhere. These interferences may greatly reduce the HNET's functioning. Further, more severe interference leads to radio link failure in mobile equipment (ME), and due to unreliable control channels, the user might not continue to use the existing service or be unable to request a new service. To avoid all these problems, inter-cell interference coordination can be used for its proper operation. FF is a bio-roused method that has been utilized for settling nonlinear optimization issues. It depends on perceptions from the social bug settlements, where every person (for example, a firefly sparkling through bioluminescence) seems to work for its own advantage, but then the gathering in general performs to be profoundly coordinated [6]. FF algorithm firefly's brightness relies upon the fitness work. The objective of the FF is to achieve effective self-coordination among BSs. Fitness esteem chooses the brightness of the BS; henceforth, the fireflies with lesser fitness esteem move towards more prominent fitness esteem. BSs are considered haphazardly conveyed fireflies [7]. In [8], the constraint of firefly measurement is repealed by utilizing the hybrid approach of particle swarm optimization (PSO) and firefly measurement, which incorporates the usefulness of PSO in firefly measurement and, additionally, works on the conduct of fireflies engaged in the search for a better solution.

In [9], the author sets up a cluster for BS using the FF algorithm that minimizes the cost function. The objective of the FF algorithm is to observe the particle position of those outcomes for the best assessment of guaranteed fitness function. At the point when groups are framed with the FF algorithm, all bunch hubs initiate the transmission of information to their individual group heads. Group heads gather information from hubs and move to the base station for less energy utilization [10]. The author in [11] has suggested a method for energy-efficient clustering where they start by producing the irregular population of n fireflies. Every particle computes its light force (fitness). Without fail, all fireflies are arranged by request, diminishing as indicated by their fitness and view as the best one. Later, with a pairwise correlation of the light power, the firefly with less light pushes toward a more splendid one. This development relies on the distance between two fireflies. During the process, the best-up-to this point arrangement is refreshed until terminal measures are fulfilled. Firefly measurement is by all accounts an ideal improvement apparatus peculiarity because of the impact of the allure work, which is exceptional to the FF conduct [12]. Firefly doesn't retain or recollect any set of experiences of better circumstances, and they may wind up missing their circumstances [13]. Energy consumption of the node is estimated on the premise of transmission. The energy examination additionally demonstrates that the energy consumed-through correlation among LEACH, direct transmission, and the fast firefly algorithm performs better-through-less energy [14].

The Python implementation of the framework is used to assess its performance using real-world network construction datasets from a 5G operator. Through thorough simulations, the benefits given by network slicing are studied in terms of the attained data rates for V2X, blocking likelihood, and handover ratio through various mixtures of traffic types. The findings showed that when network traffic load in a region of interest and end users' quality of service are taken into consideration, appropriate resource splitting is crucial for slicing across V2X and other varieties of services.

This paper deals with the sleep mode technique used to reduce BS power consumption by the FF algorithm used to formulate the sleep technique. Interference is reduced by the FF algorithm, and the proposed FF algorithm optimizes the power consumed by the base station. The remainder of the paper is structured as follows: In Section II, the proposed model and general problem are discussed. Section III discusses the FF algorithm to formulate the sleep technique, and interference reduction is discussed. Section IV demonstrates the performance and simulation results of the proposed algorithm. Section V deals with the conclusion of the paper.

2. 5G SMALL CELL NETWORK MODEL

Let us consider a downlink model from the above fig. 1 of a HNET. In this model, each tier is considered a cellular network, with macro and small BS having their own prescribed radius. The mobile equipment that connects the concerned BS is named macro mobile equipment (MME) and small mobile equipment (SME). In Fig. 1, it is assumed that the mobile equipment is distributed uniformly, and each mobile equipment is associated with SBS and MBS. The whole frequency band is shared by both MBS and SBS, which are in dissimilar clusters. The bandwidth of the system is given by Bs, and the frequency reuse factor is one for the system.

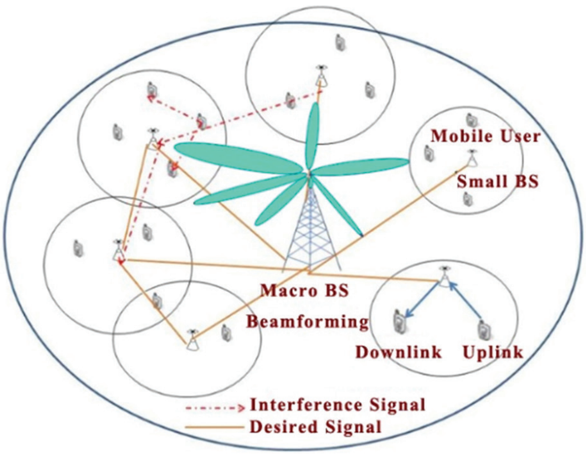


Fig. 1. Small cell and macro cell network model in 5G systems

The transmission power of $SBS\ b$, and $MBS\ m$ is given by P_b and P_m respectively. The path loss between mobile equipment and BS for HNET outdoor network is given by the equation,

$$P_L = C + 10 \log_{10} (R^{\eta}) + S_r \tag{1}$$

where, P_L is path loss between mobile equipment and BS, R is distance amid BS and mobile equipment, η is the path loss component and S_r deals with random shadowing and it is zero mean random variable. After measuring the path loss channel gain is measured by

$C_g = 10^{-P_L/10}$(2). Where P_L is the value of path loss. Next step is to determine the signal to interference and noise ratio ($SINR$). In general, $SINR$ is measured for typical mobile user w.r.t $BS\ y$ is given by

$$SINR\ (y) = \frac{Wy/Plf(|y|)}{Np+Tp-y/Plf(|y|)} \tag{2}$$

where, N_p is the noise power which is a constant, T_p is total received power from the whole network and is given by $T_p = \sum_{y\epsilon\varphi} W_y / P_{lf}(y)$ where φ is related to poisson point process where W_y is assumed as $\{W_y\}_y \epsilon\varphi$ and is given by a collection of random variables which are identically and independently distributed.

The path loss function P_{lf} is given by

$P_{lf}(|y|) = (C|y|)^{\alpha}$ with the constants $C>0$ and $\alpha>2$ (3)

In this proposed method $SINR$ is given for $ME\ e$ that connects to $SBS\ d$ as

$$\text{SINR (y)} = \frac{P_{Signal}}{P_{Interference} + P_{Noise}}$$

$$SINR_{d,e} = \frac{P_{d,e} C_{g\ d,e}}{\sum_{m=1}^{N} P_{m,e}\, C_{g\ m,e} + \sum_{b=1, i\neq d}^{M} q_{b,e}\, P_{b,e}\ C_{g\ b,e} + \mathrm{Np}^2} \tag{4}$$

Here $P_{d,e}$ is transmission power of $SBS\ d$ with $ME\ e$, $C_{gd,e}$ is the channel gain between $ME\ e$ and $SBS\ d$, $P_{m,e}$ is transmission power of $MBS\ m$ when is related with $Me\ e$. similarly $C_{g\ m,e}$ is the channel gain of $MBS\ m$ and $ME\ e$. $P_{b,e}$ is the transmission power of $SBS\ b$ when is related with $ME\ e$. similarly $C_{g\ m,e}$ is the channel gain amid $SBS\ b$ and $ME\ e$. N denotes the number of MBS and N denotes the number of SBS (N=6). Np is the noise power of the network and $q_{b,e}$ =1 implies the connection between $ME\ e$ and $SBS\ b$.

Similarly, the $SINR$ for MBS m $w.r\ t\ ME\ t$ is given by,

$$SINR_{m,t} = \frac{P_{m,t} C_{g\ m,t}}{\sum_{j=1, j\neq m}^{N} P_{j,t} C_{g\ j,t} + \sum_{b=1}^{N} q_{b,t} P_{b,t} C_{g\ b,t} + \mathrm{Np}^2} \tag{5}$$

3. POWER MANAGEMENT MODEL FOR 5G SYSTEMS

Basically, the power consumed by a base station depends on two types of power consumption. One is the dynamic power, and the other is the static power. Static power consumption at the base station is active even if there is no connection from users. On the other hand, a dynamic base station is a function of load or traffic [14]. The power consumption of SBS is given by

$$P_{b,e} = \begin{cases} \alpha P_{SBS} + P_{am} & SBS\ in\ active\ mode \\ P_{sm} & BS\ in\ sleeping\ mode \end{cases} \tag{6}$$

where, $P_{b,e}$ is the transmission power of SBS when it is related with $ME\ e$, α is a constant which is allied with usage of data traffic. P_{SBS} is the SBS transmission power. P_{am} denotes the power consumed by SBS in active mode which is static in nature. This P_{am} is independent of the transmission power. P_{am} is the power consumption of SBS in sleeping mode. The small cell base station components are shown in Fig. 2.

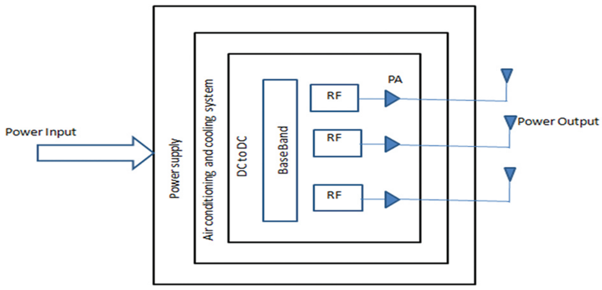


Fig. 2. Small cell base station components

4. FF ALGORITHM FOR SLEEP TECHNIQUE FOR OPTIMIZATION

The FF algorithm is a metaheuristic type of swarm intelligence technique where the behavior of FF is followed. FF is a non-linear algorithm that has multiple agents and is based on swarm intelligence algorithms. The FF [15] algorithm is one that is derived from nature, as it is enthused by the behavior of fireflies. Fireflies are insects or beetles that have wings that produce light and blink at it. This light does not have any ultraviolet or infrared frequencies; rather, it is produced chemically from the lower abdomen, which is called bioluminescence. The FF algorithm, which was first introduced by Yang [16], is based on bioluminescent communication and was assumed with the following formulations:

Fireflies will be attracted by every other firefly in spite of the sex since it is unisexual in nature.

Brightness and attractiveness are proportional to each other; a brighter firefly will attract a less bright firefly. However, when the distance between two fireflies is increased, their attractiveness decreases.

On the other hand, it will move around randomly if the level of brightness is the same.

Thus, when we relate the brightness of fireflies to their objective function, their attractiveness makes them competent to divide themselves into smaller groups, and each subgroup swarms around the neighborhood model.

Here, the brightness B_r of a firefly at a point is defined as

$$B_r(p)\ \alpha\ f_n(p) \tag{7}$$

Where p is dimensional point in dimensional space and $f_n(p)$ is the fitness function which is defined. $B_r(p)$ is directly proportional to the value of $f_n(p)$.

As discussed, earlier attractiveness A_r depends on the distance amid two fireflies and the brightness is indirectly proportional. The attractiveness decreases between the fireflies as the distance increases. Thus, attractiveness equation is defined by

$$A_r(p) = A_{ro}e^{-\gamma d^2} \tag{8}$$

where, A_{ro} is the attractiveness at d=0 and γ is constant value. The movement of firefly a toward more attractive firefly b is given by the equation

$$p_a^{i+1} = p_a^i + A_r e^{-\gamma d_{ab}^2}\left(p_b^i - p_a^i\right) \tag{9}$$

where, d_{ab} is the distance amid fireflies a and b, i is the iteration number.

The brightest firefly moves randomly and given by the equation

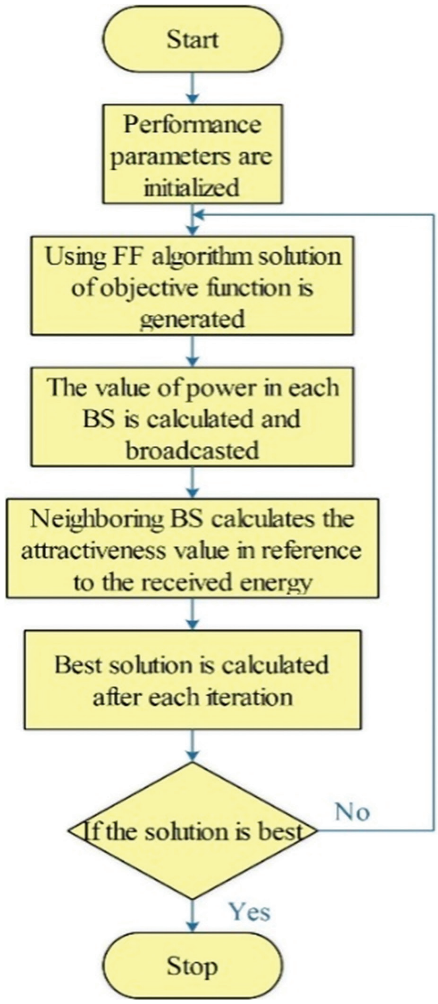
$$p_a^{\,i+1} = p_a^{\,i} + \alpha\varepsilon_i \tag{10}$$

were, $\alpha\varepsilon i$ randomization parameter.

Firefly measurement is productive and simple to execute. It is likewise reasonable for parallel execution. Nonetheless, investigations show that it is delayed in convergence and effectively gets caught in the neighborhood ideal for multimodal issues.

Likewise, the updates exclusively rely on current execution, and no memory of past best solutions or exhibitions is kept. That might prompt losing better solutions. Besides, since the boundaries are fixed, the search conduct stays very similar for any condition in all emphases. Subsequently, changing the standard firefly measurement to support its exhibition has been one of the examination issues. The network power management optimization flow in small cell 5G systems is shown in Fig. 3.

An *FF* algorithm is implemented in the proposed methodology, where power is consumed efficiently in cellular *BS*. Initially, the *BS* in the network is grouped, and every *BS* in the group shares information related to residual energy, its distance from other *BS* in the group, and the number of retransmissions. This information is used to choose the active *BS*. After every round, this information is modernized on every *BS*, and regrouping and macro-*BS* selection are carried out. In the firefly-based method, the value of residual energy plays an important role, as this value is shared between the other *BS* in the network. The distance between any two *BS* in the group is measured. Based on the values of residual energy and later, an active *BS* is found in the network, from macro *BS* to Femto *BS*. The *BS* with low power is enticed toward the high-power *BS*, and the attractiveness factor is measured. Any two Femto *BS* having the same power can be selected randomly. For 5G beam-forming heterogeneous networks, an outage probability analysis is proposed, which consists of a cellular multi-layer network. For the proposed beamforming heterogeneous network, the connotation possibility, the number of users in a layer, and the serving *BS*s probability density function are derived [17, 18].



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5. RESULTS AND DISCUSSION

Fig. 4 displays the distribution of macro- and small-cell base station nodes in the 5G network. Macro Base Stations (*BS*s) are used as a baseline and provide uniform coverage.Micro and pico/femto (often also referred to as small) cells are equipped with lower power *BS*s which are deployed in hotspots to increase capacity, or in dead spots unreachable by macro *BS*s in order to increase coverage.

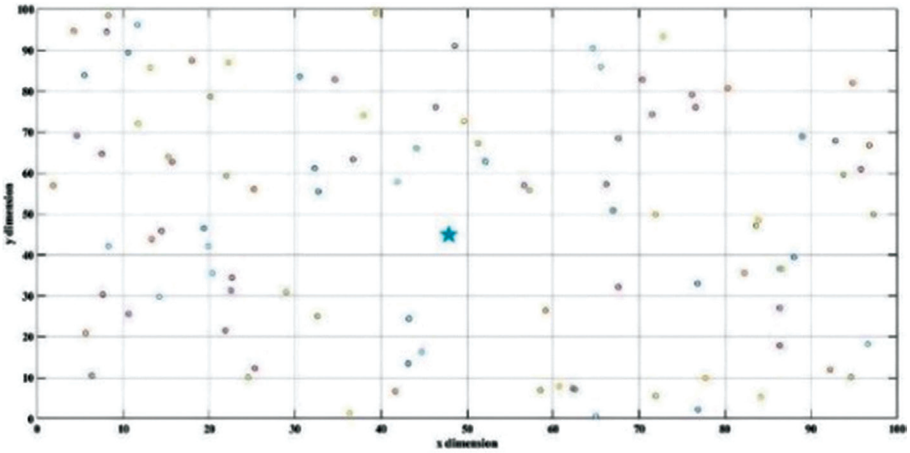

Fig. 4. Distribution of Macro and Small Cell Base Station Nodes in 5G Network

Fig. 5 illustrates the number of active base stations with 25% initial base station energy. The results imply that the proposed *FA* outperformed the existing methods. Fig. 6 shows the residual energy in a small cell 5G network with 25% initial base station energy. The total energy consumed by the base station during its operational time can be estimated by multiplying the energy consumption rate with operational time.

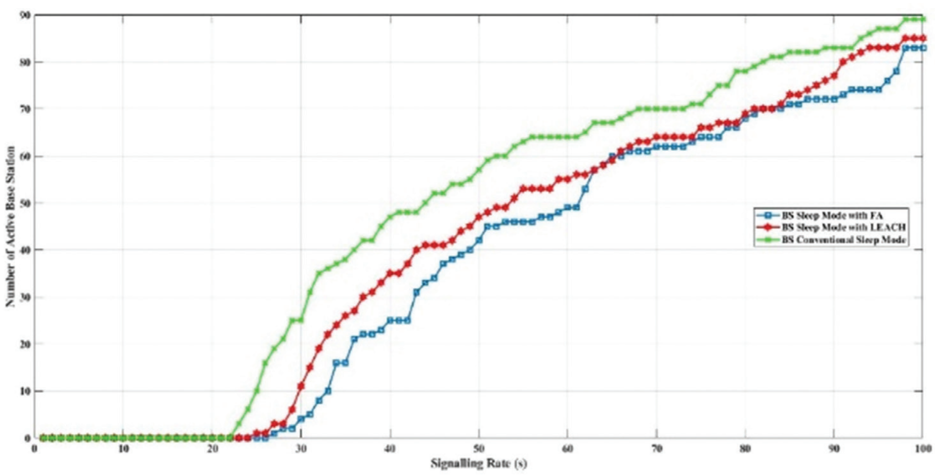

Fig. 5. Number of active base station with 25% initial base station energy

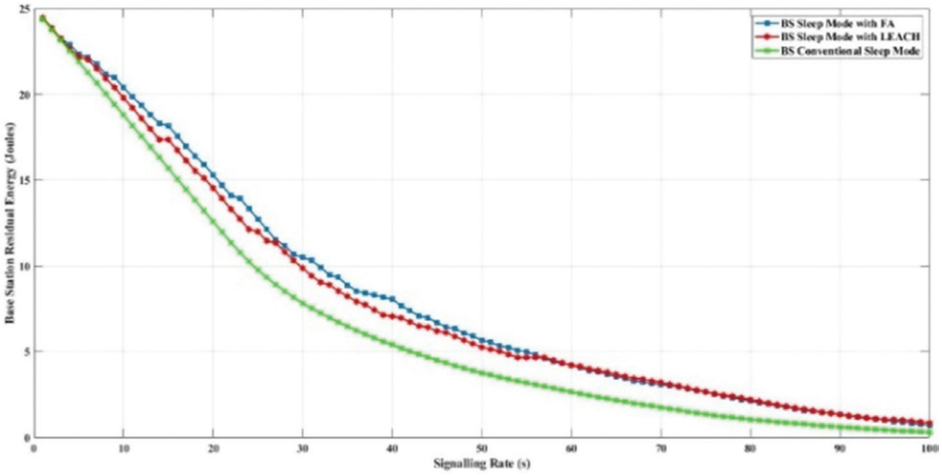

Fig. 6. Residual energy in small cell 5G network with 25% initial base station energy

The number of inactive 5G base stations with 25% initial energy is shown in Fig. 7. If a base station is considered inactive when its energy level is below 25% of the total capacity, then the number of inactive base stations can be calculated by multiplying total number of base stations with probability that a base station is inactive due to having less than 25% energy. Fig. 8 shows the throughput of a small-cell 5G network with 25% initial energy. It is denoted that the proposed *FA* has more number of throughput than other methods.

The distribution of small base stations is a dynamic process that considers the evolving needs of users, traffic patterns, and the characteristics of the deployment area. The goal is to create a flexible and adaptive network that efficiently meets the demands of 5G services.

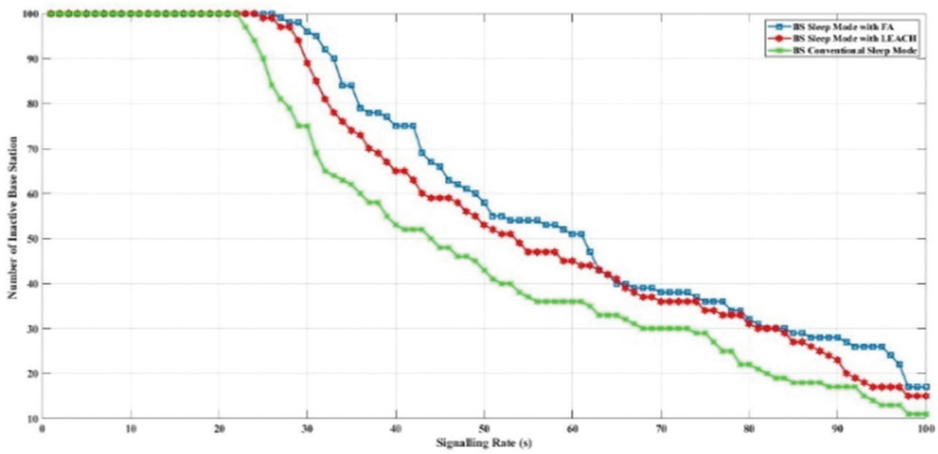

Fig. 7. Number of inactive 5G base station with 25% initial energy

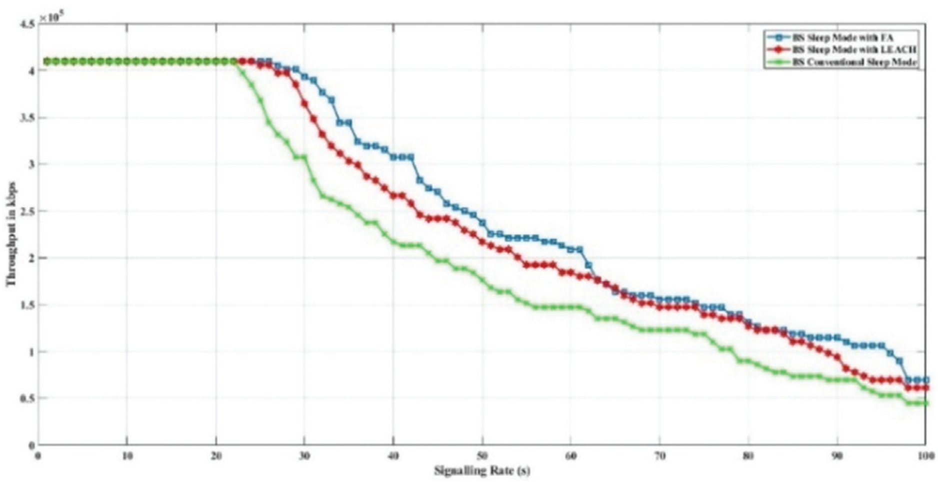

Fig. 8. Throughput of small cell 5G network with 25% initial energy

Fig. 9 displays the small-cell 5G network with 50% initial base station energy.

The residual energy in a small cell 5G network with 50% initial base station energy is displayed in Fig. 10. The number of inactive 5G base stations with 50% initial energy is shown in Fig. 11. Fig. 12 shows the throughput of a small-cell 5G network with 50% initial energy. The small-cell 5G network with 75% initial base station energy is illustrated in Fig. 13. Fig. 14 displays the residual energy in a small-cell 5G network with 75% initial base station energy. Fig. 15 shows the number of inactive 5G base stations with 75% initial energy. Fig. 16 shows the throughput of a small cell 5G network with 75% initial energy.

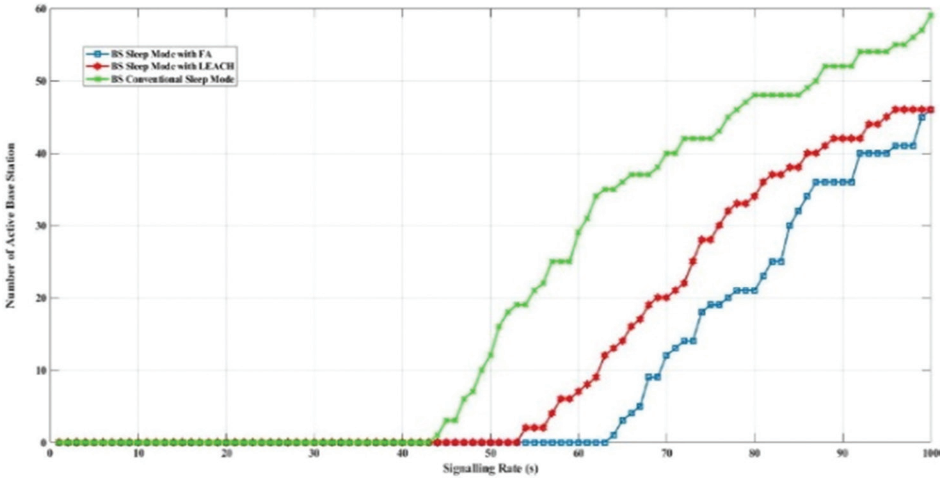

Fig. 9. Small cell 5G network with 50% initial base station energy

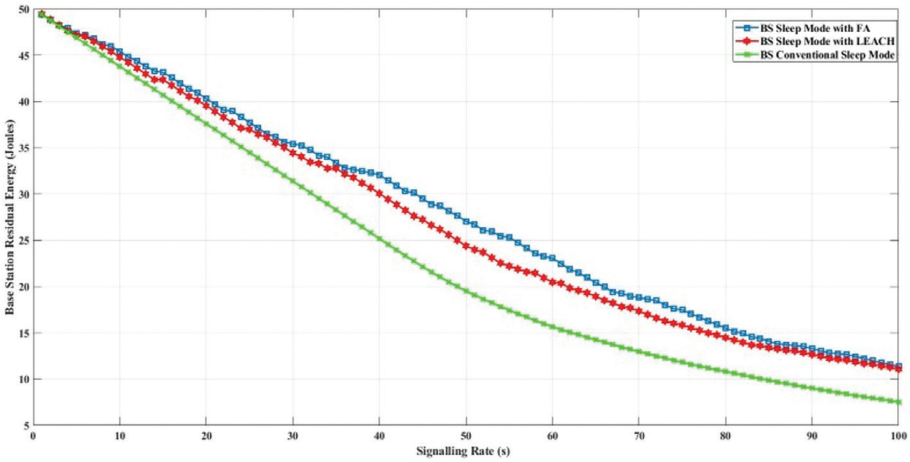

Fig. 10. Residual energy in small cell 5G network with 50% initial base station energy

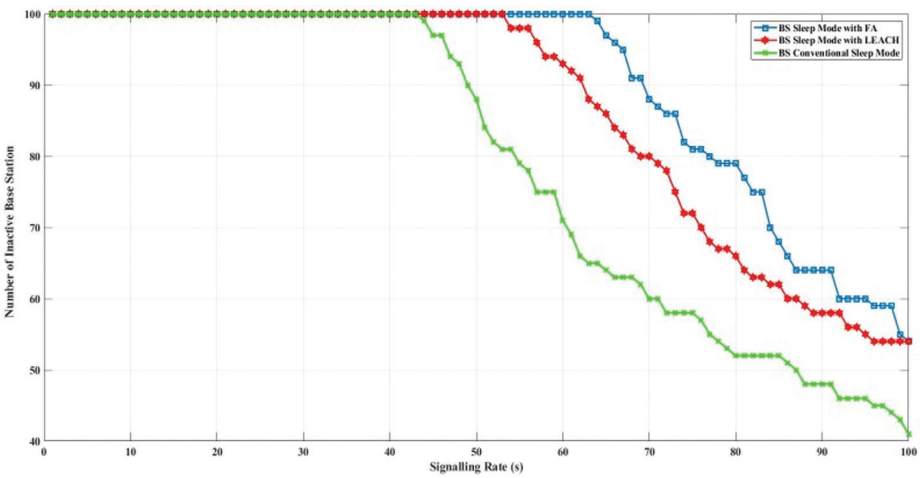

Fig. 11. Number of inactive 5G base station with 50% initial energy

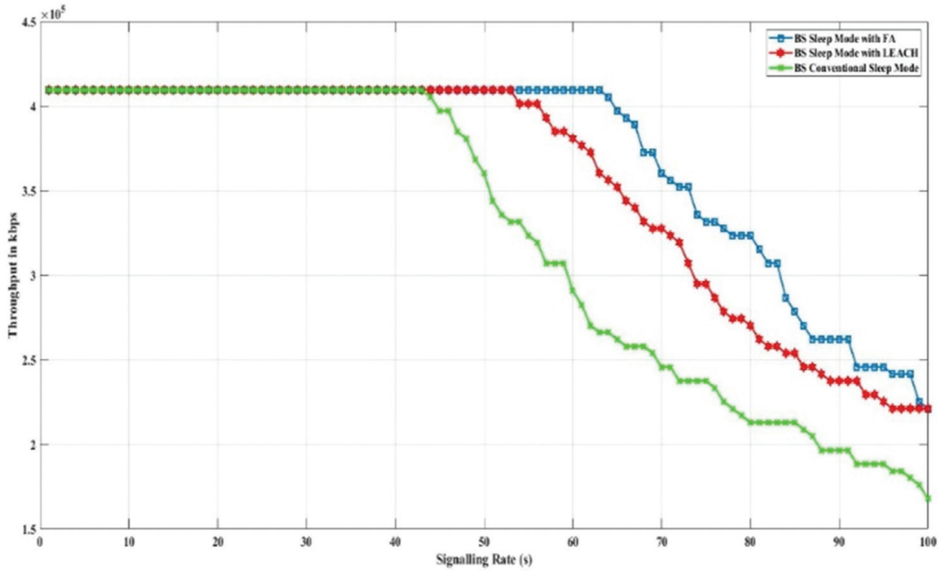

Fig. 12. Throughput of small cell 5G network with 50% initial energy

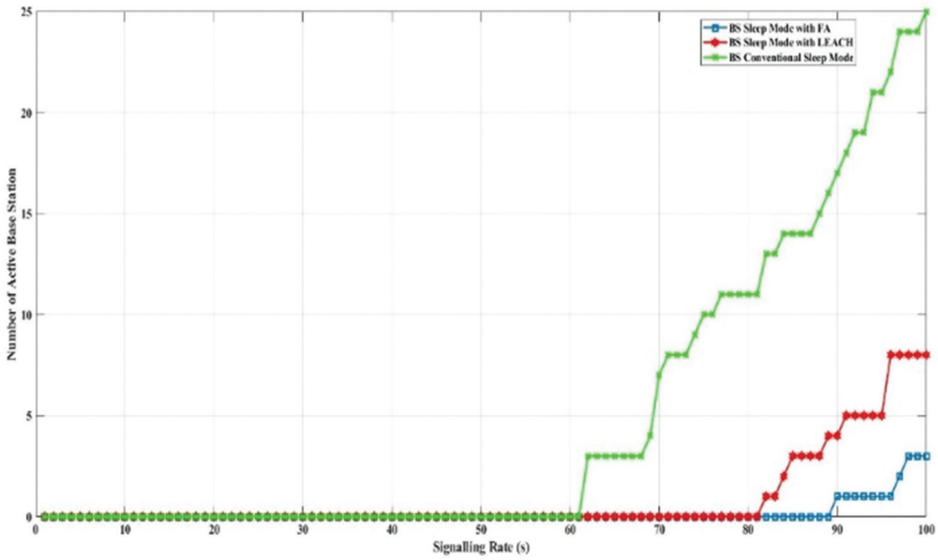

Fig. 13. Small cell 5G network with 75% initial base station energy

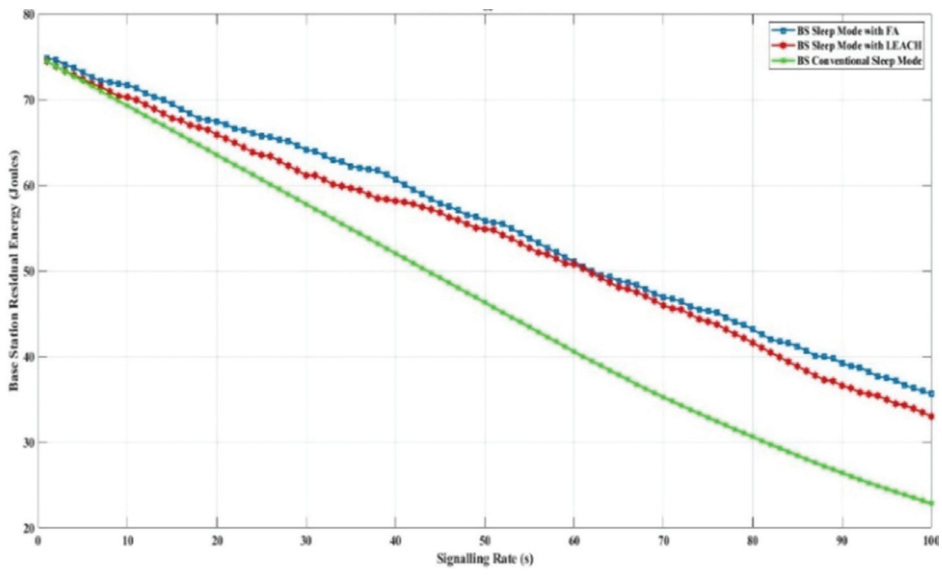

Fig. 14. Residual energy in small cell 5G network with 75% initial base station energy

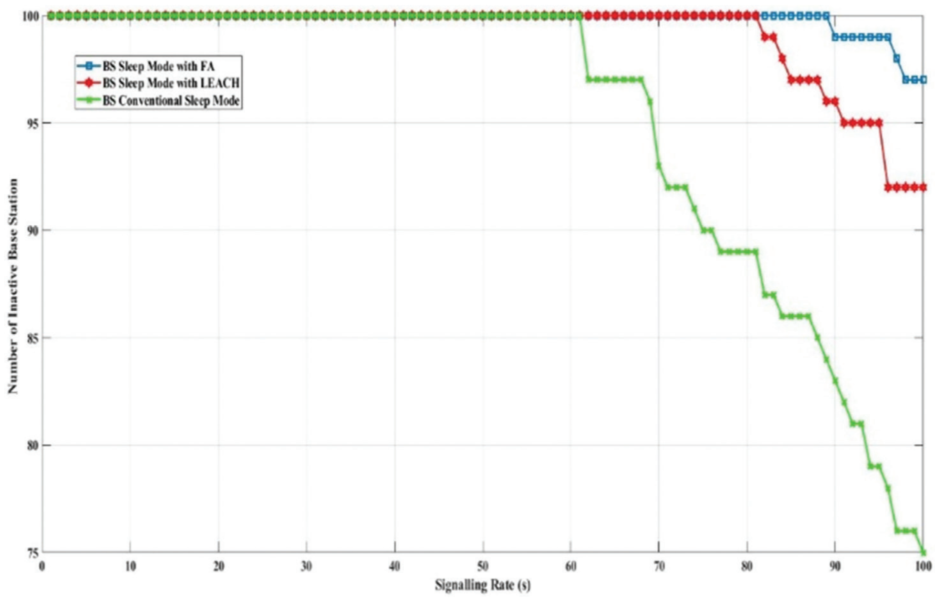

Fig. 15. Number of inactive 5G base station with 75% initial energy

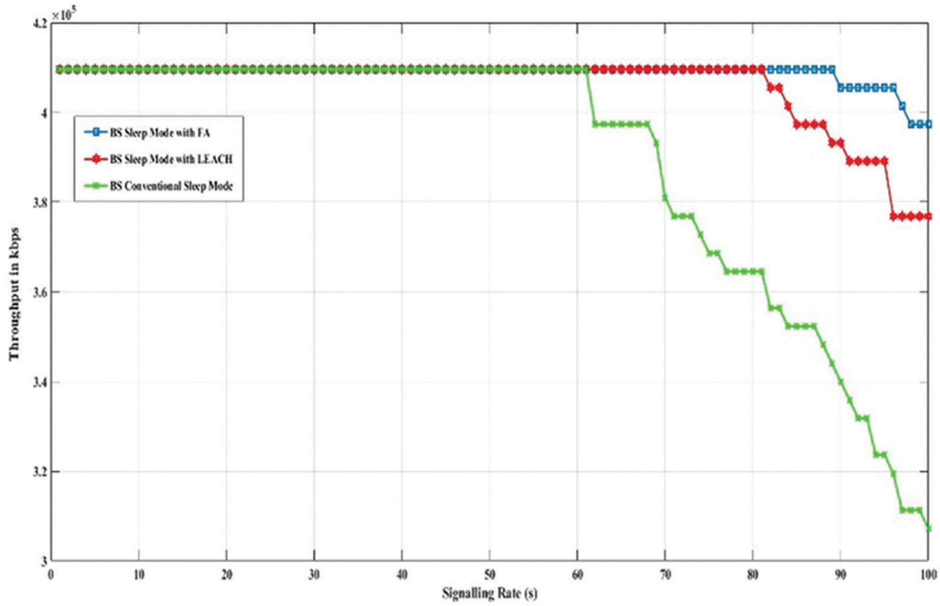

Fig. 16. Throughput of small cell 5G network with 75% initial energy

Fig. 17 displays the small-cell 5G network with inverse Gaussian traffic arrival. Actually, in an inverse Gaussian traffic arrival model, the inter-arrival times of packets follow an inverse Gaussian distribution. This type of traffic model can be used to represent bursty traffic patterns commonly observed in communication networks. Fig. 18 shows the residual energy in a small-cell 5G network with inverse Gaussian traffic arrival. This process typically involves simulation or analytical modeling, where you simulate the behavior of the network over time and observe the energy dynamics. Depending on the complexity of the model and the simulation environment, this calculation may require advanced tools such as network simulators or custom software implementations. Fig. 19 displays the number of inactive 5G base stations with an inverse Gaussian traffic arrival. This process typically involves simulation or analytical modeling, where you simulate the behavior of the network over time and observe the energy dynamics. Depending on the complexity of the model and the simulation environment, this calculation may require advanced tools such as network simulators or custom software implementations. The throughput of a small-cell 5G network with inverse Gaussian traffic arrival is shown in Fig. 20. The calculation of the throughput of a small-cell 5G network with inverse Gaussian traffic arrival involves modeling the traffic arrival pattern, resource allocation, and network conditions.

From this research, it is experienced that managing residual energy in small cell 5G networks with inverse Gaussian traffic arrival requires adaptive energy management strategies, accurate energy prediction models, and careful optimization to balance energy efficiency with network performance requirements. The attained results address these challenges, operators can maximize the operational lifetime and sustainability of small cell deployments while ensuring high-quality service delivery to users.

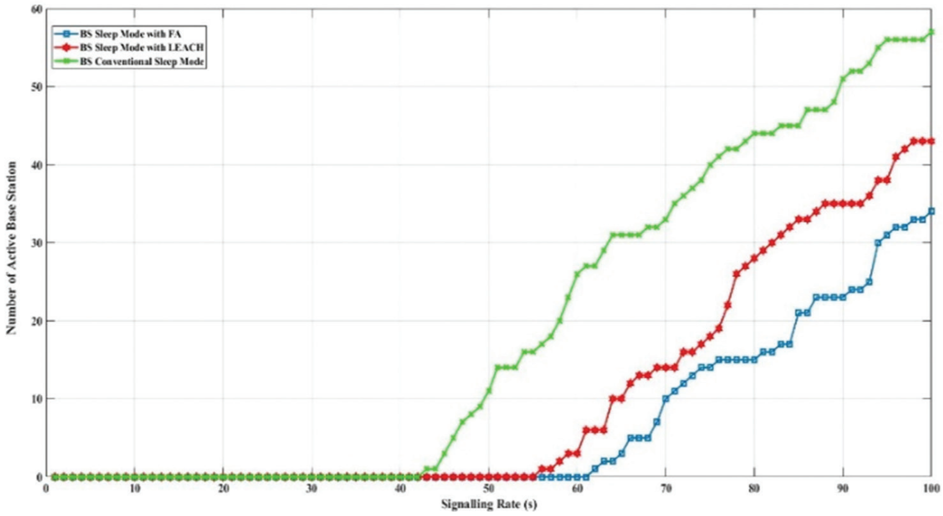

Fig. 17. Small cell 5G network with inverse Gaussian traffic arrival

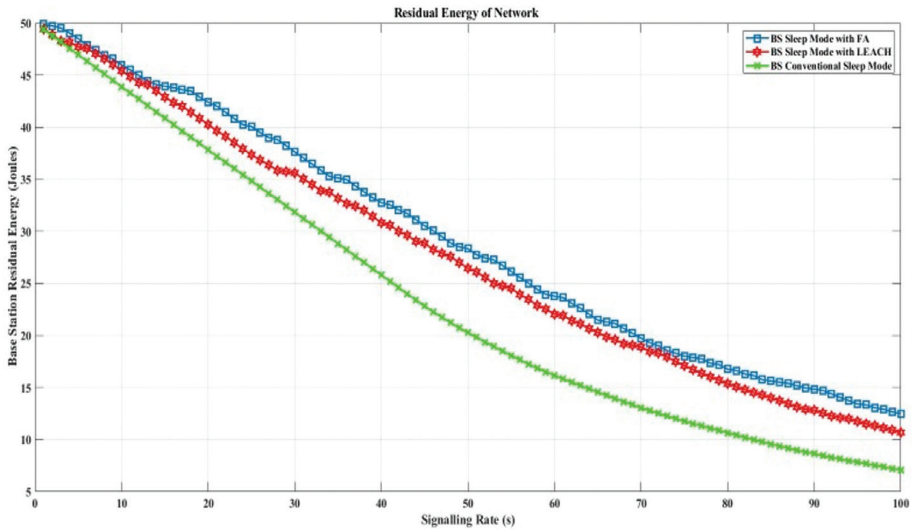

Fig. 18. Residual energy in small cell 5G network with inverse Gaussian traffic arrival

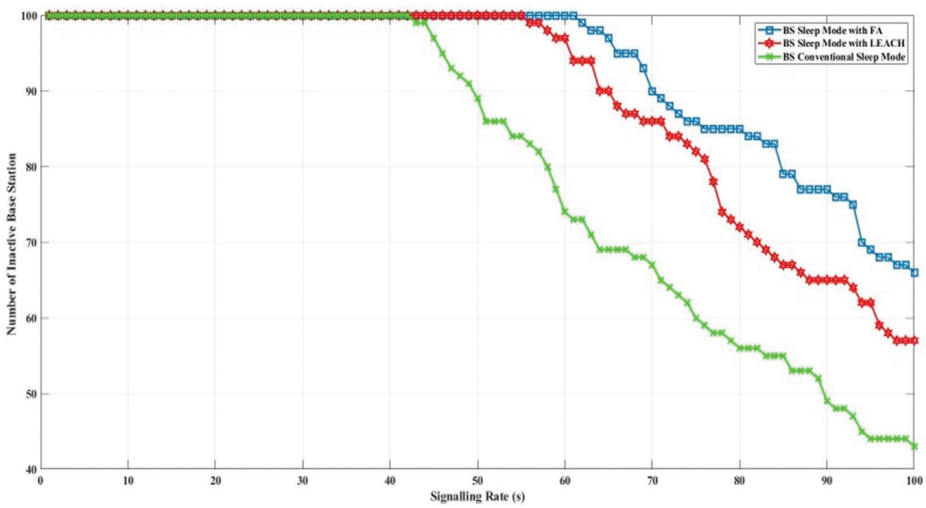

Fig. 19. Number of inactive 5G base station with inverse Gaussian traffic arrival

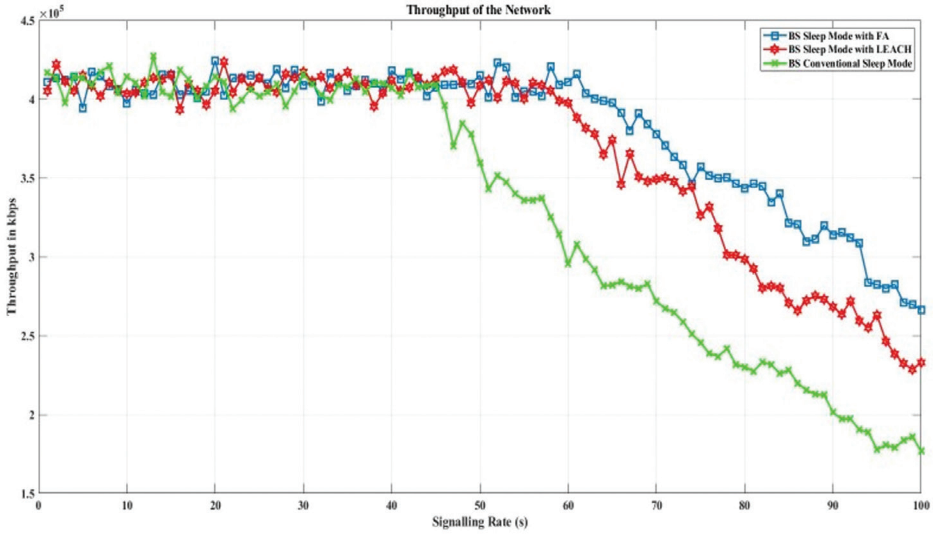

Fig. 20. Throughput of small cell 5G network with inverse Gaussian traffic arrival

In 5G cellular networks, lowering base station power consumption is an important objective for a number of reasons, including the opportunity to deploy more energy-efficient networks and environmental sustainability, as well as operating cost reductions. An optimization technique inspired by nature, the Firefly Algorithm (FF), can be used to improve a number of variables, including wireless network power usage. Energy efficiency, cost savings, environmental impact, extended network lifespan, capacity and performance optimization, adaptability to dynamic environments, regulatory compliance, trade-offs, and challenges are some possible effects and advantages of using the Firefly Algorithm for power optimization in 5G base stations. In conclusion, using the Firefly Algorithm to lower 5G base station power usage can have a variety of advantageous effects, including sustainable environmental and economic gains. In summary, leveraging the firefly algorithm for performance measurement and optimization of small cell power management in 5G networks can lead to significant improvements in network efficiency, quality of service, energy efficiency, capacity optimization, and overall network performance.

6. CONCLUSION

In order to improve interior user coverage and cell capacity in the 5G network, low-power small-cell base stations are deployed in residential and commercial buildings. However, power consumption from macro- and small-cells has grown more than the former, and this is a possible issue that the proposed 5G network aims to address. In order to save energy in 5G networks, we presented firefly optimization-based power management in this study. Comparing the suggested firefly optimization to traditional power management strategies, simulation results demonstrate a notable improvement in energy conservation with increased throughput and decreased latency. In a 5G network, cutting power and limiting interference has several advantages, including lower operating costs, environmental sustainability, better network performance, increased spectrum efficiency, and an improved user experience. These elements support a 5G network's overall performance and competitiveness.

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