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Improving Energy Consumption in 5th Generation Cellular Networks through Sleep-wake Scheme of Base Stations

Abstract

Efficient energy transfer arises in energy-constrained networks such as wireless sensor networks, satellite telecommunication networks, where wireless equipment is powered by batteries that are either non-rechargeable or difficult to recharge, as a result of consuming Energy in them should be minimized. Active base stations (BSs) began to work with a constant number, but the number changes gradually based on environmental feedback. In this process, the network coverage and energy consumption amount are monitored in each time window of t seconds. If the reduction of active stations number does not reduce the network coverage, the probability of station reduction will be increased. However, if both the energy consumption and network coverage are dropped after several stages of active stations' reduction, the automata are penalized, and the possibility of BSs' reduction will be declined. The simulation results show that even in delay-sensitive scenarios, it is possible to reach 55% and 10% higher energy efficiency (without creating additional delay) in low and medium traffic loads, respectively.

Keywords: *5th-generation networks, network energy consumption, sleep-wake scheme, Cell maginification, cellular wireless networks*

Mehrnaz Emami
Graduated with a master's degree in telecommunication electrical engineering from the Islamic Azad University, Yadgar Imam Khomeini branch - Ray city.
Mehrnazemami077@gmail.com

Dr Ramin ShaghaghiKandovan
Member of the academic staff of the Department of Electrical Engineering of the Islamic Azad University, Yadgar Imam Khomeini Branch - Shahr Ray
Ramin.shaghaghi@gmail.com

1. Introduction

A percentage of the emission of CO_2 pollutants in the world is caused by communication and telecommunication technologies, and with the development of 5G generation networks, this situation will become worse. Recently, cellular networks 5 have become the most important research topic in wireless communication in many research groups and research consortia, which leads to the advancement of research in this field.[1]

The 5th generation (5G) networks emerged as an emerging wireless technology that uses various routing protocols. The amount of energy consumption, coverage rate, load balance, packet delivery rate, communication overhead in the network, and throughput rate are among the performance measurement criteria of these algorithms. The 5G networks are widely recognized as an optimistic solution for establishing wireless communication for mobile users and a complement to wired broadband access technologies. This success is mainly attributed to the high flexibility of the network pattern, the advantages of which include self-configuration and reduction of installation costs.[2]

Lowering energy consumption and improving the coverage of wireless users are challenges for these networks, although efforts have been made in recent years to solve this problem. Coverage becomes essential when it is tried to cover the entire area in the initial layout of the base stations (BSs). In other words, the entire area should be covered by the wireless network, and each part of the area should be in the field of view of at least one station. In general, coverage could be considered as a subset of wireless network service quality. The ability of each method to reduce energy consumption can be very effective in evaluating the efficiency and acceptability of that method.

Sleep-wake techniques of BSs are performed to reduce energy consumption by selectively turning off some base stations during off-peak hours. BSas have the largest share of energy consumption in cellular networks. Therefore, it is possible to decide to turn off/on some network elements by monitoring the network traffic. Sleep mode should not reduce the network coverage since the sparse deployment of BSs leads to less coverage and random traffic pattern, making sleep mode undesirable.

Choosing a proper sleep-wake scheme significantly impacts network performance, especially regarding energy consumption and lifespan. The optimal selection of the main active stations in the proposed algorithm is made through the ant lion optimizer (ALO) meta-heuristic technique. This helps to reduce the energy consumption of the network without violating the proper coverage in different areas of the network.

Most of the solutions proposed to increase energy efficiency focus on the base station as an element of the network that consumes the most energy, and it deals more with network aspects in order to use each of the base stations at the appropriate time. It is clear that the less the number of active sites, the more energy we can save.[3]

The most critical challenges in cellular networks are the lack of spectrum dedicated to cellular communications, high cost and increased energy consumption in communication systems, and as a result, increased carbon dioxide emissions[4]. Network challenges include spectrum efficiency, high data displacement and mobility, non-stop coverage, and diverse service quality requirements[5].

Although radio access techniques must cope with the increasing growth of traffic loads and demands on network capacity, energy efficiency is still critical for wireless networks. Global warming due to communication technologies has motivated scholars to search for ways to reduce energy consumption. Both industrial and academic studies have focused on cellular networks as a significant energy-consuming component. Until recently, the main goal of cellular networks (as it started in 1970) was to maximize the throughput, spectral efficiency, and quality of service (QOS) parameters, while energy consumption did not matter. Another motivation to find methods of optimizing energy consumption in cellular networks was to reduce the cost bills due to energy consumption[6].

Network capacity could be increased by many small cells, large-scale antennas, and broader bandwidth in the millimeter wave band, but reducing energy consumption is very challenging. Therefore, energy efficiency is used as the main evaluation index of the 5G system. Various indicators of energy efficiency depend on the system, number of channels, and optimization goal[7]. For example, a network may be single-cell or multi-cell in terms of limited coverage or capacity. Coverage is critical for systems developed in rural areas, and energy efficiency is measured as the ratio of average power consumption to network coverage area. The traffic loads of systems in urban areas are often high. A standard measure to evaluate energy efficiency is the ratio of the total number of bits sent to the energy consumed in a specific time.

Cell magnification is an energy consumption optimization technique in which the base stations adaptively change their coverage area based on the changes in the traffic situation. This network layer technique adjusts the cell size based on the traffic situation through antenna tuning angle, height, and transmission power(17). The advantage of this method is the simple switching between the sleep-wake scheme in BSs, which is applied to balance the traffic load of each station and reduce energy consumption. As the traffic load in a specific cell increases, the cell is shrunk to reduce the coverage area and minimize possible interference. For this purpose, the optimal radius is extracted for each cell at any time according to network traffic information[8]. Figure 1-1 shows the change in cell radius and, consequently, the change in the cell coverage area. Sleep mode techniques are also implemented to save energy by turning off the BSs during off-peak hours. The largest share of energy consumption in cellular networks is allocated to BSs. These methods help to make decisions about turning off/on specific network elements by monitoring the network traffic load.

On the other hand, scattered deployment of BSs leads to less coverage and random traffic pattern, which disfavors sleep mode[9, 10]. In the sleep mode technique, the BSs must be integrated; that is, the active stations perform the work of the inactive stations. BSs selected for the sleep mode distribute their channel resources to their active neighbors. Active BSs use the acquired resources cooperatively to cover mobile users around the sleeping BS. Here, quality of service requirements - including changes in signal-to-noise ratio (SNR) depending on the distance between mobile users and the BSs of the service provider - must be carefully monitored. Users connected to a sleeping BS must connect to a new active BS. This process needs to guarantee service quality (SQ) since SQ should not be reduced by implementing the sleep operation of that BS[11, 12].

Energy-efficient transmission in energy-constrained networks, such as wireless sensor networks, comes from ad-hoc networks and satellite communications, where wireless equipment is powered by batteries that are either non-rechargeable or difficult to recharge and therefore, their energy consumption must be minimized. Since the development speed of battery technology is much slower than the increase in energy consumption, mobile terminals in cellular systems must be energy efficient. Especially with the recent growing demand for mobile multimedia communication, energy limitation has turned into the main problem of smartphones [13-15].

A method of reinforcement learning is the learning automata. The learning automata try to find the answer without any information about the desired action (i.e., considering the same probability for all actions at the beginning). An automata action is randomly selected and applied in the environment. Then the environment response is received, and the probability of actions is displayed according to the learning algorithm; the above procedure is repeated [16].

Several challenges in these networks include limited bandwidth, mobility of Mobile Node, low security, path Loss, fading propagation, shadowing effect, loss of electromagnetic signals by blind spots behind objects and tall buildings, and co-channel Interference[17]. The next generation of wireless networks is required to develop and increase the data rate to fulfill future telecommunication needs. It is predicted that the volume of data traffic of mobile phones and wireless equipment will increase up to 10,000 times in the next decade; This increase will be caused by 91 billion devices connected to the network in 2020, while all these devices need data access and sharing anywhere and anytime[18]. Challenges of the rapidly increased number of devices connected to the network are resolved by increasing the capacity to improve energy efficiency and the cost of proper use of the frequency spectrum and comprehensive control of these devices by 5G cellular telecommunications; therefore, 5G cellular communications have been established with the following goals[18]: In the academic environment, device-to-device (D2D) communication was presented for the first time to use a multi-path relay in the cellular network[19], and then, the potential of D2D communication to increase the spectral efficiency of the cellular network was investigated [15, 20]. Later, other uses of D2D communication were introduced, including machine-to-machine (M2M) communication and cell load reduction.

3- System Model

The most critical challenges in cellular networks include the scarcity of spectrum allocated for cellular communications, high cost and increased energy consumption in communication systems, and as a result, increased carbon dioxide emissions. Energy-efficient communication will be one of the primary needs in 5G wireless systems. Spectral efficiency, high data rates and displacement, uninterrupted coverage, and varied quality of service requirements are among other challenges of these networks.

Cell magnification (CM), a network layer technique that adjusts cell size based on traffic conditions, is a way to optimize energy consumption. In CM, the base stations adaptively change their covered area based on the change in the traffic situation. This is done by adjusting the angle of the antenna and its height and transmission power. Very simple to switch between sleep-wake schemes in the BSSs is the advantage of learning automata. This helps to balance the traffic load of each station and reduces energy consumption. As the traffic load in a cell increases, the cell is shrunk to minimize the coverage area, which minimizes the possible interferences in turn.

Sleep mode techniques also aim to save energy by turning off BSs during off-peak hours. As mentioned before, BSs use the highest energy in cellular networks. Deciding to turn off/on the network's elements depends on the traffic. On the other hand, sleep operation becomes unfavorable due to the sparse deployment of BSs, which leads to less coverage and random traffic pattern. In the sleep mode technique, BSs need to be integrated (i.e., inactive stations' tasks should be completed by the active stations). The BSs selected for sleep mode share their channel resources with their active neighbors. Active BSs use these acquired resources collaboratively to cover mobile users around the sleeping BS. Here, it is necessary to carefully monitor the quality of service requirements, such as changes in signal-to-noise ratio (SNR) depending on the

$$X(t) = [0, cumsum(2r(t_1) - 1), cumsum(2r(t_2) - 1), \ldots, cumsum(2r(t_n) - 1)]$$

provider. User connection refers to the connection of mobile end users with BSs in an energy-efficient way. Users connected to a sleeping base station must connect to a new active BS. This process needs to guarantee the quality of service, and the service quality should not be reduced by

$$r(t) = \begin{cases} 1 & if\ rand > 0.5 \\ 0 & if\ rand \leqslant 0.5 \end{cases}$$

l sleep modes (ASMs) are defined as the gradual shutdown of the BS, depending on the activation/ deactivation times of its various elements. This transmission period defines the different levels of sleep mode that could be implemented in the new 5G networks. A management strategy based on the Q-learning approach, presented by Salem and colleagues [79], allows finding the best combination and duration of the ASM level depending on the traffic load and the network operator's policy regarding energy reduction versus delay. Given the simulation results, even in delay-sensitive scenarios, it is possible to reach higher energy efficiency in low and medium traffic loads, by 55% and 10%, respectively, without causing additional delay.

4- Proposed Plan

A technique to create a sleep mode in BSs is cell magnification, which aids BSs to adaptively change their coverage area based on the change in the traffic situation. As a network layer technique, cell magnification adjusts cell size based on traffic conditions. For this, the angle of the antenna, its height, and transmission power are adjusted. The advantage of this method, which balances traffic load and reduces energy consumption,

is its simple implementation for switching between sleep and wake modes in BSs. As the traffic load increases in a cell, its size is reduced. The covered area is also reduced, and possible interference is minimized.

In the first phase of the proposed plan, the average traffic sent by each central station (workload) in the previous phases is calculated. For this purpose, the number of users and packages they send at specific times will be monitored. As shown in Figure 1, the input data is like a time series collection of statistical data at equal and regular intervals. Statistical methods using this kind of data are called time-series analysis methods. In the decision block, the amount of load is determined for each BS.

In the second phase, the meta-heuristic algorithm of the ant lion optimizer (ALO) is performed to select the best combination of active BSs to serve mobile users. ALO simulates the conflict between ant lions and ants in a trap. To model this conflict, ants should move in the search space, and ant lions are allowed to hunt them, and their fitness is increased by using traps. Since ants move randomly in nature when searching for food, modeling the ants' movement is performed by a random motion: [2]

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where **cumsum** calculates the cumulative sum, **n** is the maximum number of iterations, **t** represents the step of the random walk, and **r(t)** is the random function defined as follows:

)2(

where **t** represents the random walk step, and **a rand** is a random number generated with a uniform distribution in the interval [0,1]. Ants are like particles in PSO or people in GA. The location of an ant refers to the parameters of a particular solution. The outline of a solution in ALO is demonstrated in figure 1. According to this figure, creating different combinations of stations helps to activate or de-activate other BSs.

3	6	2	7	9	4	11	1

Figure 1. The structure of a solution in the proposed plan

Given figure 1, the size of a solution could be equal to the maximum number of active BSs. The values of the matrix cells are the numbers of BSs in the network as active stations. Due to the high density of stations in the environment and the exponential number of possible solutions, it is impossible to generate and evaluate all possible solutions. Therefore, ant lion optimizer as a meta-heuristic method is used. In addition to ants, it is assumed that ant lions are also hidden somewhere in the search space. In reinforcement learning, a goal is specified for the learner, who learns to reach it through trial and error in the environment. One kind of reinforcement learning is called stochastic learning automata. A stochastic automaton tries to find the answer to a problem. At the same time, it has no information about the optimal action (i.e., considering the same probability for all its actions at the beginning). An automata action is randomly selected and applied in the environment. Then the environment response is received, and the probability of actions is displayed according to the learning algorithm. This above procedure will be repeated. In the third phase, the maximum number of active stations (used as a fixed input in the ant optimization algorithm) is updated based on the reward-punishment mechanism.

Stochastic automata start with a limited number of actions, a random environment that the automata are associated with, and a learning algorithm used to learn the optimal action. A stochastic automaton is defined as a quintet SA=[1 G, (]; Here, r is the number of automata actions, $\alpha \equiv \{\alpha_1, \alpha_2, ..., \alpha_r\}$ is the set of automata actions, $\beta \equiv \{\beta_1, \beta_2, ..., \beta_m\}$ is the set of automata inputs, $F \equiv \phi \times \beta \rightarrow \phi$ is the function of generating a new state, $G \equiv \phi \rightarrow \alpha$ is the output function that maps the current state to the subsequent output, and $\phi(n) \equiv \{\phi_1, \phi_2, ..., \phi_k\}$ is the set of internal states of the automata at the moment n. At the beginning of the automata activity, the probability of its actions is equal to $\frac{1}{r}$ (where r is the number of automata actions).

An increase/decrease in the number of base stations is considered a possible process, and each time, a chance is assumed for increasing/decreasing the number of active stations based on the value of this probability number. Active BSs are initialized with an initial constant, but new values are assigned gradually based on the environment's feedback. In this phase, network coverage and energy consumption are monitored in each time window of t seconds. If the reduction of active stations does not reduce the network coverage, the probability of station reduction will increase. This is a reward mechanism in the following relationship.

)3(

$$p_i(n+1) = p_i(n) + a[1 - p_i(n)]$$
$$p_j(n+1) = (1-a)p_j(n) \qquad \forall j, \quad j \neq i$$

Nevertheless, if both the energy consumption and network coverage are reduced after several stages of active station reduction, this process is automatically penalized, and the probability of BSs reduction will slake. This is updated based on the following formulas:

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$$p_i(n+1) = (1-b)p_i(n)$$
$$p_j(n+1) = \frac{b}{r-1} + (1-b)p_j(n) \qquad \forall j, \quad j \neq i$$

Therefore, active network stations are dynamically increased/decreased to match the network workload.

5- Simulation

The simulation is performed through MATLAB software. It is the fourth generation of programming language and helps to perform numerical calculations. The term MATLAB refers to the matrix-oriented approach of the program, where even single numbers are treated as matrices. To achieve high speed and performance, MATLAB core is written in C language, but its graphical interface is implemented in Java. MATLAB programs are primarily open source; MATLAB is a computer interpreter, not a compiler. MATLAB's strength is due to its flexibility and ease of use.

Additionally, the manufacturing company and various groups, including worldwide universities and engineering companies, add various practical toolboxes to it every year, which has improved its efficiency and popularity. The simulation includes 250 network users deployed in a 30-meter environment with uniform distribution. There are 25 active/inactive base stations in this area. The transmission power of each station is up to a radius of 5 meters. One hundred rounds of user packages are sent to specified destinations. Features of the system for implementing the proposed algorithm are depicted in Table 1. Simulation parameters are cited in Tables 2 and 3.

Table 1. System specifications to implement the proposed algorithm

Features	Value
CPU	Core i5
RAM	4 GB
OS	Windows 7

Table 2. Simulations parameters

Environmental simulation parameter	Value
Network size	30*30 m2
Distribution of nodes in the environment	random
Number of network users	50, 100, 150, 200, 250
Implementation periods	100 rounds
Number of BSs	25

Table 3. Ant-lion optimizer's parameters

Simulation parameter	Value
Maximum number of repetitions	MaxIt=50
Population size	100
Length of a solution	Maximum number of active stations
Values of solutions	Station number

First scenario: Checking energy consumption in the network to cover users

To check the optimality of the energy consumption in the proposed plan, a simulation of 100 seconds was performed, and the performance was compared in terms of the nodes' energy consumption. In Figure 2, the energy consumed by the network is lower than the basic plan. Using ALO and the best combination of BSs as active access points have reduced the network's energy consumption.

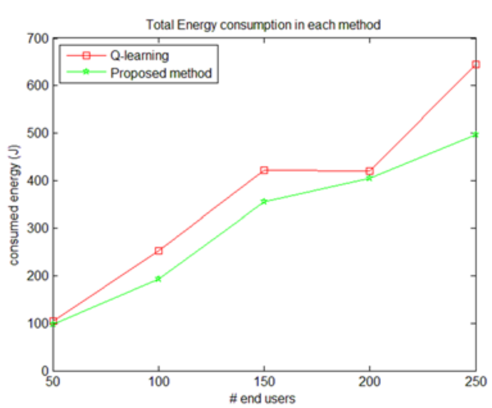
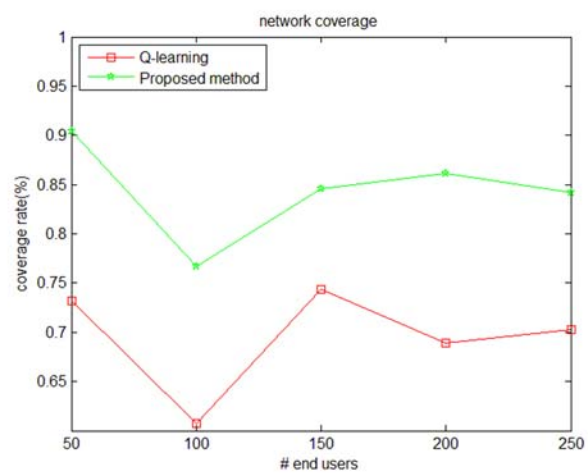


Figure 2.Performance of the proposed plan in terms of the network's total energy consumption

Although reducing the number of active access points has lowered energy consumption, the network throughput rate will drop if the network coverage drops in different areas. Throughput is a significant criterion in communication techniques. In the second experiment, the percentage of covered users in the field of view of at least one active station was recorded, and the values of each plan were compared throughout the simulation run. In Figure 3, the percentage of users' coverage in the proposed plan is higher, which means that the appropriate selection of active nodes has avoided reducing the network coverage and increment of the packets re-sending due to loss.

Figure 3. Performance of the proposed plan in terms of the coverage rate



If there is a strong connection between users and BSs, the mobility of nodes will have less impact on packet loss. However, if proper coverage is not created for users, more packets will be lost, primarily due to the unavailability of next-step nodes in the multi-step forwarding of data to the destination. By increasing active BSs, the connection becomes more muscular, but the energy consumption in the network also increases.

We would like to know whether the proposed plan covers more users by changing the number of active stations. In other words, we want to evaluate the performance of two schemes with limited active base stations.

In order to fairly measure plans' performance, energy efficiency, as a further indicator, was used to determine the energy consumed by each plan to cover users. Energy efficiency is defined as dividing consumed energy by the number of covered users. Regarding Figure 4, energy consumed per covered user is lower in the proposed plan, which refers to its higher energy efficiency.

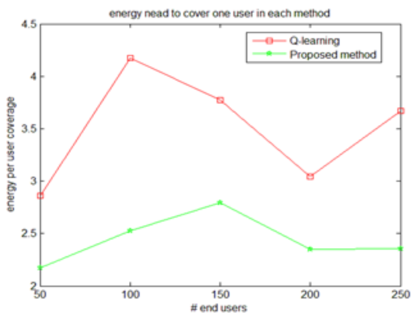


Figure 4: Energy consumed per user coverage

In the simulation, after recording the percentage of covered users who were at least in the field of view of an active station, the values of each plan were compared during the duration of the simulation. The percentage of user coverage in the proposed plan was higher than the basic plan, so with the proper selection of active nodes, reducing the network coverage and increasing the resending of packets due to loss is avoided. The performance of both plans was also evaluated in the presence of limitations to have the number of active stations. For this, another criterion was used as energy efficiency (the result of dividing the amount of energy spent by the number of covered users). Energy consumed per covered user in the proposed plan was lower than the basic plan; In other words, the energy efficiency of the proposed plan was higher.

MATLAB R2014 was used in the simulation of the proposed plan. The simulation includes 250 5G network users deployed in a 30-meter environment with uniform distribution. In this area, there were 25 active/inactive stations. To evaluate the optimality of the energy consumption in the proposed plan, its performance was compared with the basic plan in terms of nodes' energy consumption. Since energy consumption was reduced, it was concluded that the ant lion optimizer and learning automata have successfully chosen the best combination of active BSs.

6-Conclusion

The proposed plan was implemented with the aim of optimal selection of active access points while attending to the high accuracy and accuracy of traffic routing, interference, rate adaptation, and channel assignment. For this purpose, the meta-heuristic technique of the ant lion optimizer was performed. This plan helps to reduce the energy consumption of the network without violating the proper coverage in different areas of the network. Also, using learning automata, the maximum number of active stations (used as a fixed input in the ant lion optimizer) is updated based on the reward-punishment mechanism. Stochastic automata operate with a limited number of operations and a random environment that the automata are connected with, and it learns the optimal operation using a learning algorithm.

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