

Energy Harvesting in Cellular Radio Access Networks based on Q- Learning

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Abstract— In the modern communication world, capacity of future mobile networks will continuously rise for enhanced data traffic and high reliability. The current evolution trends in 5G networks and beyond impose drastic increase in energy consumption and therefore, a high level of carbon footprint by industry network infrastructures. Modern 5G wireless communication can be a potential driver for machine learning (ML) and artificial intelligence architecture at network edge. Herein, we investigate the performance and evaluation analysis of cellular radio access networks (RAN) simulated and based Q-learning approach by turning on-off some base stations (BSs) to achieve enhanced energy savings in a cellular RAN. In this work, we study the BS switching actions, considering traffic load variations. We formulate the network models as action state, environment and reward. It was shown that the proposed learning scheme results in efficient energy saving under varying workloads.

Keywords— cellular network, energy harvesting, radio, neural network, switching

I. INTRODUCTION

Energy is very vital for our life and in modern electronics world. The energy consumption is therefore a concern in various research areas. Being a non-renewable source of energy, there is an urgent need to overcome this energy constraint in modern science and technology and human life. The demand for wireless communication services has increased rapidly over the years, resulting in a significant increase in the energy consumption of cellular networks. With the growing trend of green and sustainable communication, energy harvesting (EH) has emerged as a promising technique for powering cellular networks. EH technologies enable the utilization of ambient energy sources, such as solar, wind, and radio frequency (RF) signals, to generate electrical energy that can be used to power energy-constrained devices. Various research activities are attempted for reducing the consumption of energy after the energy crisis in 1970s [1]. So far, the energy crisis is not overcome completely due to continuously consumption of energy worldwide [2]. Therefore, energy consumption needs to be minimized and use of renewable sources of energy must be encouraged. Each country across the globe is now trying to minimum possible energy and relying on the energy from agriculture,

solar energy harvesting as well as from the waste [3]. Likewise, the energy from the fossil deposits and nuclear wastes, there is a great need to keep monitoring the energy from these sections [4].

In this way, we can make a prediction on the amount of energy to be used in advance in various areas and plan accordingly for specialized applications and usage. All these usage of energy and its prediction over years is advantageous for the government and industrialist for raising the economy of the country. The amount of energy usage depends upon many factors like water, sunlight and wind. Therefore, energy consumption is highly complex [5]. In modern science and technology, machine learning approaches are very useful for predicting the amount of the energy used over time. The machine learning approaches act like a mapping function of input to output data with high accuracy.

In modern telecommunication, there is a geometric increase in the number of smartphones and electronic gadgets promoting the mobile data services. The fifth generation technology (5G) is the key to overcome the vast data traffic and demand [1]. Other variations associated with the 5G, such as cloud radio access networks (CRAN), manage the operating expenditures, and inter-cellular noise to overcome the data rates and energy consumption [2]. The 5G cellular mobile communication services boast to provide thousand times higher data rates than existing cellular systems. Therefore, new network architectures and applications, like internet of things are crucial. A popular trend in 5G technology is large scale distributed cells deployment as base station. This trend is coined as network densification. However, this type of trend for getting specified goals based on the modern 5G approach is very tough to achieve due to the increased energy crisis and environmental issues.

All these issues in advanced wireless communication can be overcome by several approaches as done in the past, such as network plan and deployment, switch off and on technology, radio resource and component level optimization, and finally use of renewable sources of energy [6]. Among these mentioned techniques, the one with sleep mode is highly regarded as efficient one for energy saving strategy. In [5], authors proposed

multiobjective optimisation method in large distributed multiple input multiple output (MIMO) systems. Presently, over 90% of the power is consumed by base stations (BSs) of RANs [4]. This is because of the deployment of the BS based on peak traffic loads. Mostly this BS are on active state regardless of the dynamic traffic load variations [7]. Valerdi et al., proposed a method to manage the power consumption of the BS which is part of the renewable energy resource and (solar, wind etc) [8]. The authors in [9] focused on C-RAN by using reinforcement learning and applying switch on-off techniques to save energy. In [10] authors showed the chance of energy saving by algorithm and simulations. In [11] and [12] authors studied how to alter the active state of BS to inactive mode dynamically, based on the expected traffic loads. In this work, we propose algorithm for energy harvesting by using a multiple agent system. In this approach, each agent has its own independent decision. Within this framework, we propose a machine learning approach with distributed multiple agents based algorithm, widely known as Q learning [12].

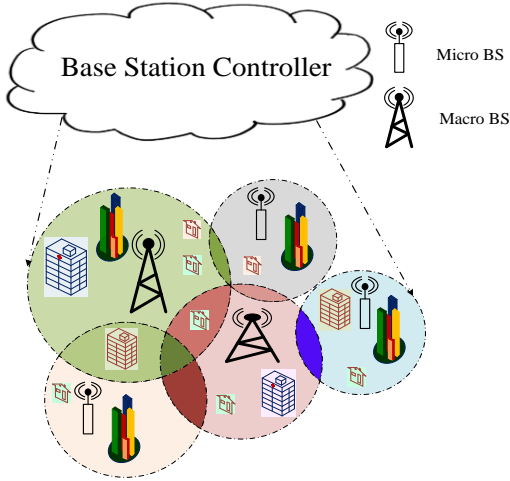


Figure 1: The framework of cellular radio access networks

In this approach, each of the cellular networks (agent) operates by resource management. We propose to maximize the energy efficiency. The framework of cellular networks is shown in Fig. 1. We adopt a cellular radio access network's for energy harvesting approach in this work. This paper presents a novel approach based on Q-learning for energy harvesting in cellular radio access networks (RANs). The proposed method aims to maximize the total harvested energy in the network while ensuring that the network performance meets certain quality of service (QoS) requirements. In this paper, we crack this problem by reinforcement learning (RL) [11-14]. A RL approach has one benefit that is there is no requirement to have a prior knowledge the traffic loads.. We proposed the novel ML based Q-learning method is to save energy. The BS controller first check variations of the traffic load based on the Q-learning. Subsequently, it can select one of the switching actions and then reduces or increase the balances repetition of the same action on the basis of the required cost which aims is to save energy. After several actions and receiving the costs, the controller which act as a agent how to turn on-off the BSs. Additionally, the ML method, the switching scheme is would improve energy efficiency

of networks. The learning operation is further enhanced by Q-learning. In the proposed methodology, ML methods is used as reward function for Q-learning techniques.

The rest of the paper is ordered as follows. System model is present in Section II. In Section III and Section IV, we discuss the energy saving pattern and simulation result respectively. Finally, conclusions are present in Section V.

II. SYSTEM MODEL

In this section, we consider cellular RAN usually comprises of numerous BSs while the traffic loads of these BSs are generally unstable, thus often making BSs under-utilization. The cells are further divided into two types such as macro and small (micro) cells. In such scenario, macro cells base station (BS) is attached to the power grid providing energy to whole cells. The micro cells are also deployed to enhance the system capacity as needed e.g., home, university, school, hospital etc.

A. Power Consumption Model

A BS comprises of many power components like processor, amplifier, transceiver, backhaul link and air conditioner tool. The total power consumption, P_c , can be calculated as follows [16]

$$P_c = B \cdot (BM_x \cdot P_a + P_{tran} + P_p + P_{gen} + P_{link} + P_{ac}) \quad (1)$$

where B represent the number of cell, BM_x is transmitting antennas per cell, and P_a is power if amplifier, P_{tran} is , transceiver power, P_p , P_{gen} , P_{link} and P_{ac} are the power consumptions of the processor, generator, link tools, and air cooler respectively.

We maximize the throughput T of the whole network by assuming the traffic intensity and coverage constraints as [17]

$$\max T = \sum_{i=1}^k T \quad (2)$$

$$\text{s.t. } 0 \leq P_c \leq P_{max}$$

$$\rho_i \leq \rho_{max}$$

$$\bigcup_{i=1}^k G_i = U$$

where ρ_i indicate effective traffic intensity for cell i , G_i denote the area served by cell.

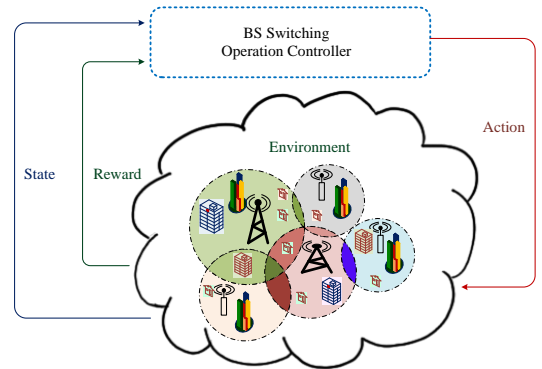


Figure 2: Working Concept of Reinforcement Learning

Hence, we study RL methods to crack energy saving problem without demanding the previous knowledge of traffic loads and precisely apply the q-learning algorithm. As the name denotes, it encompasses four components: action, state, environment, and reward as shown in Fig. 2. These microcells are operated through the energy harvested from the sun, i.e., solar energy monitored by Q learning agents.

We choose a reward function here to achieve the desired solution of the optimization problem. There are various proposed reward functions in the past using co-operative learning, independent learning [8-10, 19-20]. The QoS constraint of the macro cells was considered to optimize the sum capacity of the entire network. The cooperative Q learning has also been verified to optimize the capacity of macro cells without designating a reward function in a dense network. The use of reward function ensures a fair allocation of resources in Q-learning approach at base stations.

III. PROPOSED ENERGY SAVING SCHEME

A. Q-learning on/off switching algorithm

Here, we employ Q-learning approach. We have N distributed users for making decisions in either on or off condition independently.

As described in previous section, we consider cellular radio access networks of N agents (users). All the devices are monitored via a multiple agents system. The goal of this proposed method is to learn with environment by means of a Q-learning approach. In Q-learning system, the value function is saved in a Q-table which is expressed as

$$Q(a^t, b^t) \leftarrow Q(a^t, b^t) + \alpha \left[r(a^t, b^t) + \gamma \max_{a_1} Q(a_1, b_1^t) - Q(a^t, b^t) \right] \quad (3)$$

where α and γ is the learning rate and the discount factor respectively. $Q(a^t, b^t)$ is the state-action pair; and $Q(a_1^t, b_1^t)$ is state-action pair of next state.

B. Definition of State, Acton, Reward function

State: The state b is expressed as

$$b_i^t = [B_i^t, J_i^t, K_i^t] \quad (4)$$

where B_i^t is renewable energy source during day time and night, J_i^t represent the level of battery, K_i^t is the state of the load for i -th cell in time t .

Action: The actions A contain two actions of on state and off state of the controller. When a controller is turned off, the users connect to the macro BS. Although, the macro BS unable to contribute service, they will be leave and wait for decisions.

Reward function: A reward function is expressed as:

$$r_i^t = \begin{cases} 0 & J_i^t < J_{th} \\ 1/J_i^t & J_i^t \geq J_{th}, \text{ OFF state} \\ vT_i^t & J_i^t \geq J_{th}, \text{ ON state} \end{cases} \quad (5)$$

where T_i^t is the normalized throughput of i th cell in slot t , and J_{th} is a threshold value on the battery level. Thus, the controller can be turned off and offload the macro BS. The second line represent that the reward is proportional to the inverse of the energy buffer level when the controller is in *off* state to save energy. The third line represent that the reward is directly proportional to the v times of throughput when the controller is '*on*'. After learning, controller will remain on state. In third line, constant v is used to balance throughput and energy saving.

During the training phase, the users use the energy data to generate the Q-tables offline, these Q-values are used to generate the Q-tables for the micro cell users in online mode. This proposed training algorithm is given in Table 1.

Algorithm 1: Proposed Training Algorithm Framework

Start
1. Initialize state-value function
2. Train $Q(a^t, b^t)$
3. Calculate current $Q(a^t, b^t)$
4. Choose action a^t and state b^t
5. Calculate new state and reward value based on q-learning
6. Find the traffic loads accordingly and update state $b^t \rightarrow b_1^t$
7. Update the state-value function (3);
8. Stop

The given algorithm describes a Q-learning approach for achieving energy savings in cellular radio access networks (RAN) by turning on-off some base stations (BSs) based on traffic load variations. The algorithm is as follows: First step involves initializing the state-value function, which represents the expected reward for each state and action. In second step, the Q-function is trained for the given state-action pair (a^t, b^t) . The Q-function estimates the expected reward for each action in a given state. In third step the current Q-value for the chosen state-action pair is calculated. Next we choose action a^t and state b^t based on the current state of the network and the Q-function. In the fifth step the network moves to a new state based on the chosen action a^t , and the reward value for the new state is calculated using the Q-function. In next step the traffic loads are determined based on the new state and the state is updated accordingly. In seventh step the state-value function is updated based on the observed reward for the chosen action in the current state. Finally the algorithm stops when a stopping criterion is met, such as reaching a maximum number of iterations or a desired level of energy savings.

IV. SIMULATION RESULTS

The cellular RAN network of N distributed agents and we confirm the energy saving by proposed q- learning scheme under practical configurations. We assume the power consumption of the components of a BS are P_a is 10.4 W, P_{tran} is 30 dBm, P_p is 100 W, P_{link} is 80 W P_{gen} is 384 W, P_{ac} 690 W. We consider the propagation channel of this network by modified Hata model [18]. The goal of the proposed algorithm is for each agent to learn, through the environment, an energy saving scheme via Q-learning technique. Precisely, the energy consumption is defined when few BSs are switched off since our simulation starts. This explanation is reasonable because it show the energy efficiency enhancement, which is our goal of an energy harvesting.

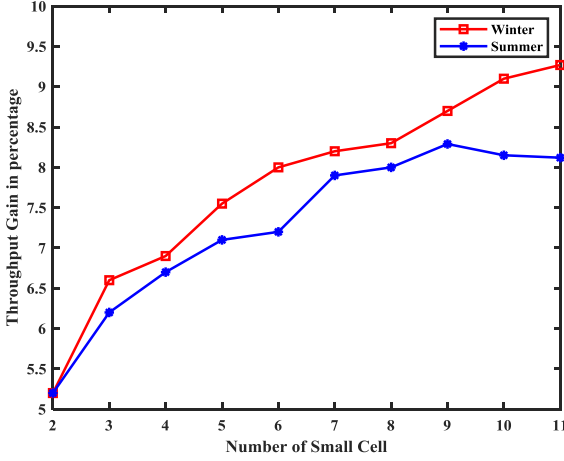


Figure 3. Throughput gain [%] of QL with number of small cell

Fig. 3 shows the average throughput gain of Q-learning as a function of number of small cells. The system throughput gain by Q- learning is upto 9.5% (during the winter). Furthermore, it rises with the number of the small cells as more users get more traffic.

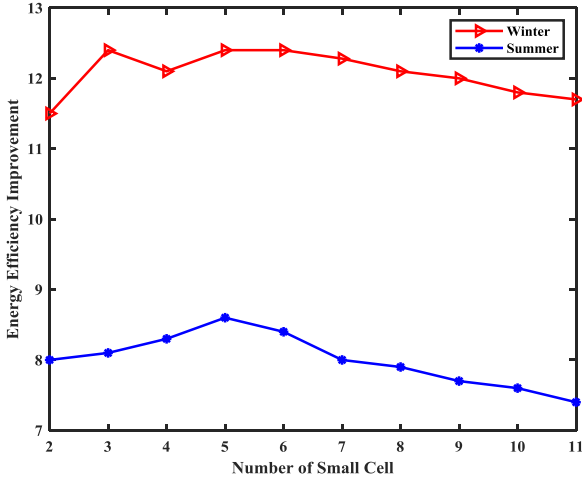


Figure 4. Energy efficiency improvement by QL method

Fig.4 represents the energy efficiency improvement of Q-learning algorithm with the number of small cell. QL significantly gain, up to 14% in the winter months. In the summer, the algorithm is not showing saved energy, since the harvested energy is sufficient for the entire day. Therefore, Q-learning has nearly similar performance.

V. CONCLUSION

We employed Q learning approach to formulate the proposed algorithm for managing the energy harvesting for cellular radio networks. We proposed the algorithm and reduced power consumption at the base station applying switching operations under varying traffic loads . Our simulated results show the encouraging and viable approach. The proposed algorithm considers the design goals at maximum and enhances the energy efficiency appreciably. However, there are certain aspects that need to be further highlighted, such as the impact of cellular network on the decisions made for careful synchronization of the common goals. Further exploration of various functions is needed to achieve the gains in performance objectives for a large number of smaller cells by using the energy efficiency into the learning.

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