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Hybrid Firefly Optimization with Double Q-learning for Energy Enhancement in Cognitive Radio Networks

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Abstract

The key feature of IoT is connecting various objects together through the internet. IoT is a wide network which interconnects various devices and sensors and helps to carry out wireless communication in cost effective way. Connecting several objects of heterogeneous nature is a major challenge in IoT paradigm which are addressed by cognitive radio networks by meeting the connectivity demands with improved spectrum efficiency. Energy efficiency is prime factor which needs to be considered in CR networks. Battery powered IoT devices which are deployed in remote areas suffer with limited network lifetime. One way of enhancing the energy is by employing data aggregation and clustering which is implemented using Double Q-learning algorithm and a bioinspired heuristic Firefly Optimization (FO) is used for optimal spectrum allocation with less energy consumption and increased network capacity. Major IoT models adopts usage of data clustering and energy deprived model to address the problem of maximum energy consumption. Thus, by combining Firefly optimization with Double Q-learning efficient energy utilization is ensured. The simulation is performed to show the throughput, lifetime and network traffic which is compared with ant colony optimization and proves to be better energy efficient.

Keywords: Energy Efficiency Optimization, Firefly Optimization Algorithm, Wireless Communication, Cognitive Radio Networks.

1. INTRODUCTION

In wireless communications cognitive radio networks provides an effective solution to reduce spectrum insufficiency in wireless communication with its efficient channel selection. In current scenario demand for accessing radio spectrum is increasing with various new wireless networks. To improve the quality of service cognitive radio network identifies communication nodes and modifies the parameters of communication schemes. Cognitive networks have emerged as a solution for the for identifying and usage of licensed spectrum that falls underutilization category. A cognitive radio network consists of Primary Users (PU) and Secondary Users (SU). At present energy efficiency is considered as the major issue in various wireless networks. Traditionally sensor nodes are powered by batteries which are not cost-effective also network lifetime is less. Secondary users can utilize the free channels or vacant spectrum with incorporation of different technologies without interfering the licensed primary users. CR networks can adapt to statistically varied input and utilize vacant channel efficiently by consuming less energy. Green communication is becoming a trend; in wireless systems energy efficiency is becoming an important factor. In this work Hybrid Firefly Optimization (HFO) is combined with Q-learning is employed for achieving optimal energy consumption, throughput and increased network lifetime, minimized network jamming. Firefly algorithm offers utilization of network capacity to the maximum by allocating contention free channels to the secondary users. In cognitive radio networks data aggregation is a best way for enhancing energy modeling. By increasing the network lifetime and adopting green communication network performance can also be increased [1]. Spectrum allocation problem is solved using firefly algorithm by optimizing the fitness function thereby improving the network capacity. The aim objective of cognitive radio is to maximize the spectrum utilization by adopting dynamic spectrum allocation algorithm [2]. To eliminate the interference between the spectrum users, current policies allocate fixed spectrum slice to each wireless application. Due to the fixed licensing policy only 6% of spectrum is utilized temporally and spatially [3] Firefly algorithm is utilized to reduce energy consumption by maximizing the utilization of communication channels and data aggregation is performed by employing double Q-learning. Clustering is used to deal with huge number of nodes in the network. Based on the operational parameters and geographical assumptions nodes are grouped. Firefly algorithm is adopted in this paper for maximizing the channel utilization with less energy and is compared with ant colony optimization.

The further sections of the paper is structured as follows. Section 2 describes the previous research about energy conservation in CR networks. Section 3 describes the problem statement. Section 4 describes the proposed firefly with Q-Learning for IoT for achieving maximum residual energy. Section 5 Performance evaluation of the proposed method and section 6 is the conclusion with cited references.

2. LITERATURE SURVEY

In the existing communication and network fields, power is supplied to the sensor using a wired power cable, and the sensor measures data using the supplied power and shares it through a wired communication cable. In this case, the cost of configuring the network is greatly increased, and the number of sensors that can be installed is limited. As an alternative solution to this problem, a wireless network technology has been proposed that uses a battery as a power supply source by embedding a battery in the sensor instead of a wired cable, and shares data by mounting a wireless communication function on the sensor. However, even in this case, when the battery life of the sensor is exhausted, not only the hassle of replacing the batteries of numerous sensors one by one, but also the network maintenance cost is greatly increased.

The concept of the Internet of Everything [4] will soon be embedded in every industry with the advent of the 5G era, and the core of the Internet of Everything is the Internet of Things. 5G technology makes the Internet of Things possible. It can be seen that the Internet of Things has extraordinary significance in the 5G era. Wireless Sensor Network (WSN) as a key field of IoT applications, plays a role similar to the “sensory” in the IoT, and is used in many fields such as military and medical. [5] The wireless sensor network is composed of a large number of tiny sensor nodes densely distributed in the monitoring area. These sensor nodes have perception capabilities, communication capabilities and computing capabilities. They form an autonomous measurement and control network system through self-organization and multi-hop methods. The main task of a wireless sensor network is to sense and collect data cooperatively among nodes, and report the monitoring information to users; its limitation lies in the limited energy of sensors and limited communication capabilities.

Ubiquitous Sensor Network (USN) is a network configured to wirelessly collect information collected from various sensors. It attaches electronic tags to all necessary places, detects object recognition information as well as surrounding environmental information, and connects it to the network in real time to manage information [6, 7]. Research related to the USN, that is, a study on sensors and sensor networks has been around for a long time [8]. At the same time, with the development of WPAN (Wireless Personal Area Network) technology and micro-network device technology, sensor network technology is very active. In the US, this technology is being applied experimentally to home automation and ecological monitoring [9, 10]. One of them is the ZigBee Alliance. ZigBee combines low-power ZigBee transceivers with a variety of sensors to form large-scale sensor networks. While the sensor network does not require transmission of large amounts of information, long battery time and transmission coverage over a certain distance are required. In order to meet these requirements, the IEEE in May 2003 introduced a low-cost, low-power wireless Personal Area Network (PAN) technology. The 802.15.4 standard has been released. In addition, recently, it has been widely used by embedding it into a complex environment such as a home network by using the features of low power and low cost digital signal processing through a MEMS (Micro-Electronic-Mechanical Systems) system based on sensor technology. [11, 12]. Also, since Mobile IPv6 is a protocol that provides terminal mobility, signaling overhead is large when moving to another link, and a method of providing mobility by applying the Mobile IPv6 protocol to each sensor with limited power and computing power is very inefficient. [13, 14, 15].

3. PROBLEM STATEMENT

Energy efficiency and network life time are the main factors in CR networks which needs to be enhanced for flexible utilization of wireless communication channels by secondary users. Battery powered nodes meet the problem of reduced network lifetime. Energy monitoring and jamming mitigation are ensured by the proposed by the hybrid firefly optimization with double Q-Learning. With the proposed model data aggregation and energy aware features are adopted with IoT which results in maximum utilization and less energy consumption in CR networks.

4. ENERGY CONSERVATION MODEL USING CLUSTER BASED APPROACH

Consider an IoT network with every node influencing the CR characteristics. Free channels can be accessed and a set of primary channels available in the IoT network called P channels where bandwidth is represented as B. Consider a channel in P namely k for transmission. Busy transmission is labeled as $Trans_{ON}$ and a probability function is applied over $FTrans_{ON}[t]$ and the function for OFF state is represented as $FTrans_{OFF}[t]$. When CR networks transceiver cooperates with the nearing IoT node and the CR network is supposed to be OFF. Set of available channels $C_{H,}$ and the hop is mentioned as h and threshold is assigned to be minimum. Data jamming is assumed to be OFF.

$$E_{Txn}[M\ ,X]=\begin{cases} XE_{Txn}+XM_{FsE\ N^2}, N<N_0 \\ E_{Txn}\quad +\ X_{PEL\ N^4}, N\geq N_0 \end{cases} \tag{1}$$

$E_{Txn}[M, X]$ where M represents multi hop distance and X represents the data packet size, N^2 resented as environment free space, N^4 power loss in multi hop, Minimum threshold is given.

$$M_0 = \sqrt{\frac{\boldsymbol{M_{FsE}}}{P_{EL}}} \tag{2}$$

$\boldsymbol{M_{FsE}}$ Represents the free space distance, P_{EL} denoted as multipath loss, M_0 denoted as threshold

4.1 Generating Cluster Head

Cluster head formation was done with secondary users with the most expected lifetime, and cluster head selection is based on the threshold selection of that node (i.e) Cluster head selection is entirely based on the threshold selection neighboring node.

$$\text{Threshold(i)} = \frac{j_{opt}}{1-j_{opt(h.mod\left(\frac{1}{j_{opt}}\right))}} \times \frac{E_{c(r)}}{E_{avg(cr)}} \tag{3}$$

$E_{c(r)}$ denotes as current energy in a cluster

$E_{avg(cr)}$ denoted as average energy in a cluster

$E_{avg(cr)} = \Sigma \frac{C_{E(r)}}{N}$ for every node i, j_{opt} denoted as optimization with respect to the jamming attack in the cluster node h. mod represented as modulation of cluster head node with the optimal node r times are performed.

4.2 Double Q-Learning for Predicting Jammers Activity

The q-learning is the type of Reinforcement Learning (RL) algorithm employed in cognitive radio networks when there is insufficient knowledge regarding the behaviour of the jammer and the environment. It is applied to take optimal or best solution to maintain the communication without jamming. The Q-Learning consists of two phases: first phase is the training phase where the actual algorithm runs and converges to obtain the optimal defense plan. The next phase is the exploitation phase where the learned policies are applied by the agent. Online Q-Learning is considered to be effective since data packets loss occurs in off line learning since jammers ay appear and disturb the primary user's task.

$$Q[b,c] \leftarrow Q[b,c] + \alpha\left[R_{a(b,b')+\gamma\, max_a}\, Q(b',c) - Q[b,c]\right] \quad (4)$$

$$Q[b,c] \leftarrow (1-\alpha)Q[b,c] + \alpha\left[R_{a(b,b')+\gamma\, max_a}\, Q(b',c)\right] \quad (5)$$

where $0 < \alpha \leq 1$ is the learning rate that manages how new approximates combines with the older ones. The Q-value is the rewards obtained. This learning strategy updates the value of Q[b, c] with any trials until optimal convergence occur which is the training phase. Synchronous ode of Q-learning is adopted to learn the jammer strategy so as to neglect the channels that are jammed. Double Q-learning is employed for efficiently predict the jamming activity thus offering energy efficiency in CR networks.

4.3 Proposed Firefly Optimization Algorithm

Firefly generate flashes to communicate with the partner. This flashing sometimes is for warning purpose. As light intensity works in correspondence with the inverse square law which means the intensity of the light decreases as the distance increases due to absorption of the light by the air with long distance. The attractiveness manipulation and changing light intensity are considered as the most difficult issues in fireflies. Both these factors decrease with the increase in the distance. In general, if the firefly s attracts p then p moves towards s and the state of the firefly p is described as,

$$x_p = x_p + \beta_o e^{-\gamma r_{ij}}(x_s - x_p) + \alpha\varepsilon_I \quad (6)$$

where x_s and x_p are the locations of the fireflies, β_0 is the attractiveness, α is the randomization parameter, ε_i random number vector. In CR networks the channel allocation is given by the following channel availability matrix equation, $L=\{l_{x,y}|l_{x,y}\ \varepsilon\{0,1\}\}_{x\times y}$, where $l_{x,y} = 1$ only if the channel y is available to the user x else $l_{x,y} = 0$. The reward matrix and the interference constraint matrix are also manipulated. Generally, spectrum environment changes slowly whereas the user allocation is much faster location and spectrum that are available are considered to be static.

4.4 Pseudocode for the Firefly Algorithm

```
Step 1: The FA control parameter values are initialized:  γ, β, α, Rmax, nf, D.
Step 2: The initial locations of the fireflies are generated xf(f=1, 2 ,….., nf) and initialize iteration from 0.
Step 3: Objective function is defined f(x) where x=(x1,x2,x3,x4….xd)
Step 4: while t ≤ Rmax do
for s=1 to nf do
 for p=1 to nf do
    compute light intensity Iintensity at xi is determined by f(xi)
    if Iintensity ≤ Ij, then
        Move s towards p //s-firefly p-firefly
    Endif
    Attractiveness β changes with the distance
    light intensity Iintensity is updated with new solutions
    Check whether updated solutions are in limit
 end for
end for
end while
```

The fitness function used to evaluate the CR nodes performance is as follows.

Max-Sum-Reward (MSR): It maximizes the total spectrum utilization in the system regardless of fairness. This optimization problem is expressed as:

$$MSR:U(R)= \sum_{s=1}^{S} \sum_{p=1}^{P} x_{s,p} \cdot y_{s,p}$$

5. EXPERIMENTAL RESULTS

In this section, numerical results are provided to show the energy efficiency performance of the proposed model. The simulation is performed using network simulator 3 tool. Initially three levels of jamming attacks are performed against proposed firefly and the activity limits are set between (0.1 to 0.9). It is observed that the packet delivery ratio is steadily increased in the proposed method.

Table 1. Simulation Parameters

Parameter	Value
Area for simulation	1000*1000 meter
Probability	0.3
Receiver energy	$20*10^{-8}$
Nodes	100
Bandwidth of the channel	2mhz
CR IoT threshold	3db
Transmission Energy	0.1
Transmitter Energy	$20*10^{-8}$
Maximum lifetime	$3*10^{-8}$
Jamming Duration	3, 0.2, 3, 1.1, 4, 2.5, 1, 1.4 ,7, 0.1ms

Table 1. continued

The parameters, network lifetime, average energy, average throughput are used to evaluate the performance. The network parameters are setup with different CR nodes to 50 nodes. The number of packets transmitted successfully gives the network throughput. The stability period is chosen for estimating the average energy with the throughput of 100 CR nodes.

Table 2. Energy Comparison with Firefly

Nodes	Proposed Firefly	ACO	ABO
50	68.6	58.7	63.1
100	66.6	53.8	58.2
150	53.3	43.7	46.3
200	54.2	38.4	43.4

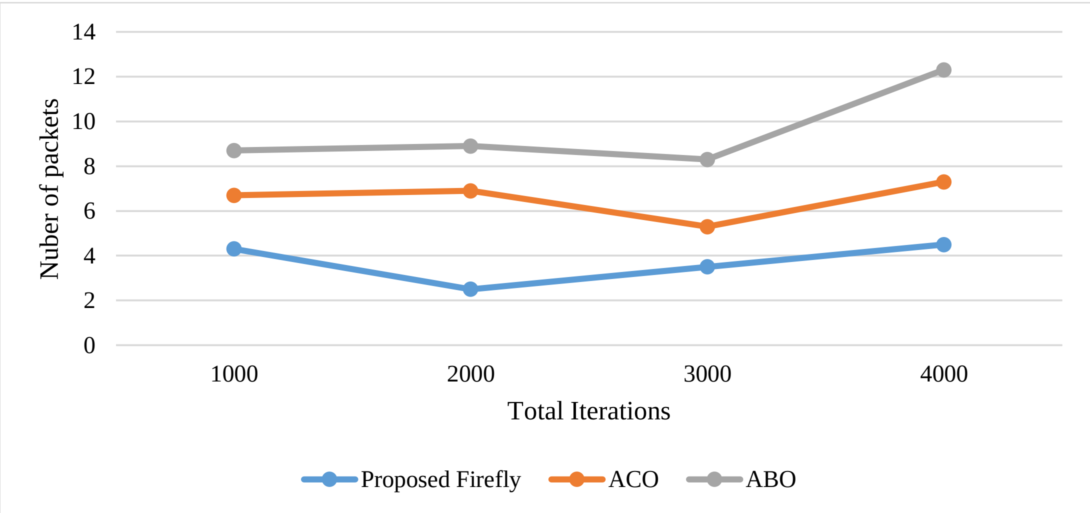

Figure 1. Throughput Analysis

The throughput is evaluated between total iterations and number of packets. The obtained values are plotted in Figure1. Figure 1 indicates the throughput performance and it is clearly indicated that the proposed technique has been significantly improved when compared with the ACO and ABO.

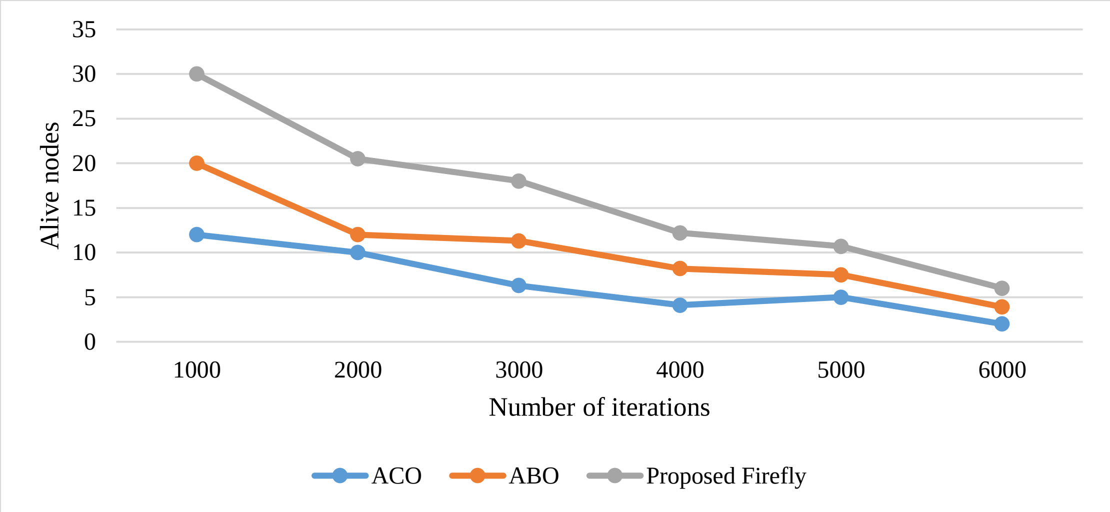

Figure 2. Network Lifetime Estimation

Figure 2 indicates the network life time performance which is compared with the node in live condition even after the attack has been happened and it has clearly indicated that the proposed technique has been significantly improved. The average energy is measured with the time taken by each node in the network to obtain the maximum duration a CR node live in the network.

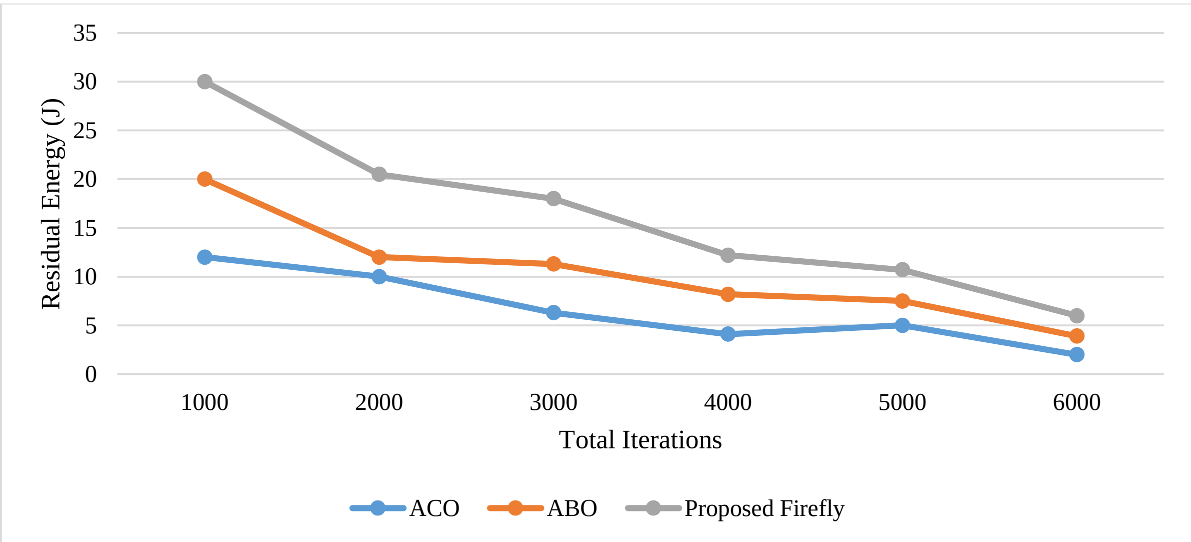

Figure 3. Residual Energy in the Proposed Model

Figure 3 indicates the energy performance and it has clearly indicated that the proposed technique has tremendous improvement. In this paper, we suppose that the secondary user has a better channel condition than the primary users so that its access into the spectrum via proposed model can greatly improve spectrum utilization without degrading performances of the primary users. The major contributions of this work are a novel energy efficiency minimization model is designed using hybrid firefly optimization with double Q-learning in cognitive radio networks.

6. CONCLUSION

This work proposed a hybrid model for efficient energy monitoring and maximum mitigation of jamming using the hybrid firefly with Q-Learning. The IoT applying this hybrid model aggregation of data using clustering and involves the usage of energy-aware devices. Received signal strength is used to estimate the condition of the channel. The proposed hybrid firefly when employed with the IoT model ensure maximum residual energy by identifying the transmitter data and data routing path. Primary user availability is measured with the received signal strength which depicts the channel condition. The numerical results have shown that proposed firefly has superior energy efficiency performance in comparison with conventional ABO and ACO.

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