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PERFORMANCE OF OPTIMIZATION METHODS FOR ENERGY EFFICIENCY IN COOPERATIVE COMMUNICATION

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Abstract. *In cooperative communication the effect of channel fading can be improved by cooperation between the user terminals and the relay nodes in wireless networks. In a Wireless Sensor Network (WSN), cooperative relaying improves the link quality with a relatively high Energy Efficiency Gain (EEG). In this paper, optimized parameters are used in WSN to enhance the EEG using particle swarm optimization (PSO) and Real-Coded Genetic Algorithm (RGA). Maximum enhancements of EEG obtained using RGA for M-ary Quadrature Amplitude* Modulation *(*M-QAM*) is 64% for M=16, 87% for M=32, and 97% for M=64 compared to EEG obtained without optimization. The superiority proposed optimization methods are verified by comparing with results without optimization and by comparing with the published results for Energy Efficiency (EE).*

Key words: *cooperative communication, energy efficiency, relay, real-coded genetic algorithm, particle swarm optimization*

1. INTRODUCTION

In cooperative communication, diversity techniques are used in a wireless network to combat the fading effects in presence of multiple users. Each user terminal has a single antenna and can't exploit spatial diversity. Therefore, instead of using multiple antennas, user terminals communicate through a number of relay nodes to use a diversity technique [1-2]. Using diversity techniques, in a fading environment, link quality between the source and the destination can be improved. The Cooperative transmission system uses relay stations in a multi-user wireless communication environment. This type of communication system reduces the power consumption of user terminals, resulting in more battery life. The applications of cooperative communication include Code Division Multiple Access (CDMA) networks, WSN, and many others. The main research problems in cooperative communication are to evaluate the performances of application based

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cooperative networks, to improve the performances of present methods of cooperative communication and to develop new efficient methods to achieve better performances. For cooperative networks in WSNs and in cognitive radio networks, low energy consumption is desired; therefore, one of the major issues in cooperative communication is energy efficiency. Cooperative communication is a distributed network and hence, the data rate and the link quality between the nodes are other issues which should be enhanced. The improved performances of point-to-multipoint communication of cooperative relaying in WSNs are another issue. Considering cooperative communication as a distributed network, the effect of fading can be minimized for spectrum sensing and spectrum sharing in a cognitive radio network [2, 3]. In [2], the probability of missed detection in cognitive networks for Rayleigh channels is reported. A survey on various cooperative networking protocols and the optimal selection methods are presented in [4]. Here, the review on the EE in multi-node scenario is also described. Both fixed networks and ad hoc networks can be accessed through cooperative communication. A sensor network consists of a number of closely spaced (positions are predetermined) sensor nodes, and these sensor devices are low-power and multi-functional nodes.

2. RELATED WORK

The WSN exploits the wireless protocol and for these battery-operated sensor nodes it is difficult to replace or recharge the batteries [5]. One can only transmit a finite amount of data with finite energy. So, the important design consideration for WSN is minimum energy consumption in the fading environment, which can be reduced using the cooperative relaying technique [6]. In [6], distributed antenna scheme is used to utilize the space diversity. Optimal packet size for data transmission in WSN is presented in [7] where the EE is used for the optimization matrix. The optimum range of transmission for consumption of minimum energy is investigated in [8] for non-cooperative communication, where for periodic monitoring purposes, multi-hop routing is used to make the network energy efficient. The problem of EE of multi-node cooperative communications in WSN is presented in [9] by exploiting space time codes. In [10], the use of energy-efficient cooperative relaying for mobile-edge computing is described using a harvest-and-offload method. To achieve fairness and maximum energy in WSN, energy-efficient node selection methods are reported in [11] where an optimal partition method is used to minimize the local energy consumption. Throughput maximization in a dual-hop communication network is discussed in [12], where the cooperative relays extract necessary energy by energy harvesting. Various types of energy-efficient relaying techniques for cooperative communication are presented in [13, 14]. In [13], open-loop architecture is used for the selection of relays, and in [14], it is reported that for small-distance communication, direct link is more energy efficient than using a relay. In [15] optimal power allocation in cooperative networks is discussed where an energy-constrained relay node acquires energy by RF energy harvesting. The optimization of EE is addressed in [16] for Unmanned Aerial Vehicle (UAV) applications where an algorithm is proposed to re-formulate the constrained robust optimization. The strategy of cooperative spectrum sensing in WSNs, using PSO, is presented in [17], where optimization is employed after analyzing the system throughput and energy consumption and establishing a mathematical model. Recently the application of cooperative relay network in underground sensor network is reported in [18], where multi-hop communication is proposed for this purpose. An algorithm, based on bit error probability, is proposed [19] to achieve significant energy saving in cooperative communication in WSN. In [20], based on improved cluster selection method, an energy-aware routing protocol is reported for cooperative multiple input multiple output (MIMO) scheme in WSN. An energy-efficient cooperative communication protocol is proposed [21] for heterogeneous WSN, based on appropriate cluster head selection. For low energy consumption, a relay selection strategy, based on the asymmetry of the social network, is reported [22] for device-to-device communication. To improve the energy efficiency of the ambient RF powered WSNs, an optimal resource allocation problem is proposed in [23].

The literature survey reveals that a better EEG can be obtained using optimization of the parameters for cooperative communication. Optimized EE depends on different parameters related to cooperative communication and not a large number of papers are available in this area of research. In this paper, first the EE is calculated using the classical theory of cooperative communication for two nodes and a relay in a WSN using *M-QAM*. The EE profile for this three-node system is investigated varying the distance from source to destination. Then the EE is optimized using PSO and RGA considering the distance between the nodes, the packet length, and the modulation level as the varying parameters in optimization. The GA is probabilistic in nature and provides global optimization with less information and can be used to solve problems that have multiple objectives or constraints. The concept of PSO algorithm is simple and easy to implement. The PSO algorithm has robustness to control the parameters with good computational efficiency compared to other heuristic optimization techniques. The PSO and RGA optimized results for EE gains are compared with the EEG, obtained without optimization. Parameter optimization gives more EEGs both in PSO and RGA optimization. Better results are obtained using RGA optimization. In this paper, in section 3, the theoretical analysis of cooperative communication, used in this work, is described with the help of effective equations. The simulated results for EE are presented in section 4 without using any optimization. In section 5, optimization of EEG using PSO and RGA is described including the brief descriptions of PSO and RGA. The optimized results are compared with the results obtained without using any optimization and with the reported results. The conclusion is presented in section 6.

3. Theoretical Background of Cooperative Communication

In order to exploit the benefits of diversity, multiple antennas are necessary at the device terminals. But in cooperative communication, instead of using a direct link from source to receiver, a relay is used to enhance the diversity gain by using single antennas at the device terminals. This networking protocol avoids using multiple antennas in users' terminals [4]. In a wireless sensor network, many sensor nodes use spatial diversity using relay nodes. Assume that in a WSN the three nodes are source (S), destination (D) and relay (R), in which source is sending data packets to destination as shown in Fig. 1. In the Direct Link Scheme (DR), source sends packets to destination directly, without using a relay and energy is consumed to support the required Signal-to-Noise Ratio (SNR).

In the Cooperative Relay (CR) scheme, a two-phase cooperation protocol can be considered. In one phase, the source transmits a data packet to the destination, and for the channel characteristics, this data packet can be overheard by the relay. If the received packet is correct in the destination, then it acknowledges back and in this phase the relay has no function. In another phase, if the received packet cannot be decoded correctly at the destination, then it acknowledges negative feedback. Here, if relay receives the data packet correctly from the source, relay sends it to the destination. Else, this packet is dropped.

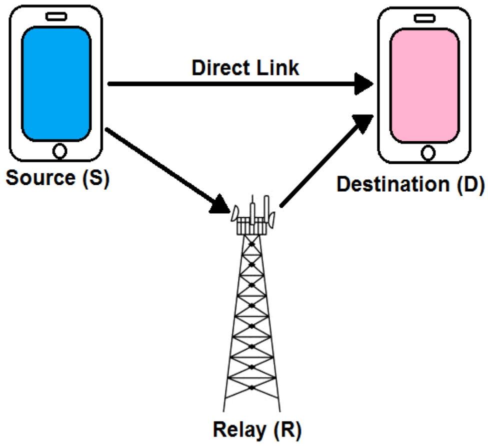


Fig. 1 General cooperative relaying model

Assume a flat Rayleigh channel between the nodes and constant transmit power (P_t) for all the nodes. The average Symbol Error Rate (SER) is calculated using the average SNR of σ_{ij} with a link between two nodes 'i' and 'j' separated by a distance r_{ij}, and the modulation level b = $\log_2 M$ bit/symbol of M-QAM modulation [14]

$$SER_{ij} = 2(1-2^{-\frac{b}{2}})\left(1-\sqrt{\frac{3\sigma_{ij}}{2(2^b-1)+3\sigma_{ij}}}\right) \quad (1)$$

Where,
$$\sigma_{ij} = \frac{P_t(r_{ij})^{-\alpha}}{N_o} \quad (1a)$$

The path loss exponent is represented by α, and the noise components are modeled as Additive White Gaussian Noise (AWGN) with variance N_0.

Packet Error Rate (PER) for a link of data packet length of ‘L’ is

$$PER_{ij} = 1-(1-SER_{ij})^{\frac{L}{b}} \quad (2)$$

So, the PER of DR is equal to the PER of Source to Destination (SD) link and is [14]

$$PER^D = PER_{sd} = 1-(1-SER_{sd})^{\frac{L}{b}} \quad (3)$$

PER of CR is

$$PER^C = PER_{sd} PER_{sr} + PER_{sd}(1 - PER_{sr}) PER_{rd} \tag{4}$$

The EE of the system (η), defined as the ratio of the number of packet bits for successful transmission to the energy consumption, is [14]

$$\eta = \frac{L_p(1 - PER)}{E} \tag{5}$$

where, L_p is the payload length of a packet and E is the energy consumption for sending a packet in DR or CR scheme. The loss factor of the power amplifier is β ($0 < \beta < 1$) and the consumption of power in the transmitter and the receiver is P_{ct} and P_{cr} respectively. The bit rate is $R_s \times b$ for the constant symbol rate of R_s.

3.1. Direct Link Transmission

To transmit one data packet of length L, total energy consumption with the DR scheme is [14]

$$E^D = (P_t(1+\beta) + P_{ct} + P_{cr}) \frac{L}{R_b} \tag{6}$$

The EE of DR is:

$$\eta^D = \frac{L_p(1 - PER^D)}{E^D} \tag{7}$$

3.2. Cooperative Relay Transmission

In this case, the total power consumption of CR for transmitting one packet can be described in three possible ways. Over the SD link the probability of successful transmission is ($1 - PER_{sd}$), the consumed power consists of the consumed power in S, ($P_t(1 + \beta) + P_{ct}$) and the received power between the D and R, $2P_{cr}$ [14]

$$P^C_{totalA} = P_t(1+\beta) + P_{ct} + 2P_{cr} \tag{8}$$

The transmission failure probabilities over the SD and the Source to Relay (SR) links with probabilities of PER_{sd} and PER_{sr} is

$$P^C_{totalB} = P_t(1+\beta) + P_{ct} + 2P_{cr} \tag{9}$$

The event indicating re-transmission by R, for the transmission failure over the SD link is

$$P^C_{totalC} = 2P_t(1+\beta) + 2P_{ct} + 3P_{cr} \tag{10}$$

So the total energy consumption to transmit one data packet with CR is

$$E^C = \frac{(1 - PER_{sd}) P^C_{totalA}}{R_b} + \frac{PER_{sd} PER_{sr} P^C_{totalB}}{R_b} + \frac{PER_{sd}(1 - PER_{sr}) P^C_{totalC}}{R_b} \tag{11}$$

The EE of CR is [14]

$$\eta^{C}=\frac{L_p(1-PER^{C})}{E^{C}} \tag{12}$$

The EEG is the ratio of the EE of CR to that of DR and is given by [14]

$$G=\frac{\eta^{C}}{\eta^{D}} \tag{13}$$

Thus both EE and EEG vary with distance between the nodes, according to the (1a).

4. Simulated Results

In this section, the simulation for cooperative communication is performed using the analytical method, described in the previous section. The system parameters, like, link distance, packet size and modulation level affect the EE and in simulation these are varied. MATLAB R2016a is used and when varying one of these parameters, and others are constant. The nodes S, R, and D are assumed to lie on a straight line and the Relay to Destination (RD) distance is expressed as $r_{\mathrm{rd}} = q \times r_{\mathrm{sd}}$ ($0 < q < 1$). In this simulation, parameter values are taken from [24], which are α=4, β=0.3, P_t=0.001 W, $P_{\mathrm{ct}}=10^{-4}$ W, $P_{\mathrm{cr}}=5\times10^{-5}$ W, $R_s=10^4$ symbol/s, $N_0=10^{-13.5}$, q=0.5, L_p=40 bit, L=56 bit, and b=4.

4.1. Impacts of the SD Distance and the Relay Positions on EE

The variations of EE and the EEG of CR and DR with different locations of nodes are presented in Fig. 2 and Fig. 3 respectively. DR is more energy efficient than CR at SD distances below 100 m. This is due to the fact that the relay consumes extra energy for cooperation and it dominates to decrease the PER of the system. At SD distances, more than 100 m, CR is more energy efficient than DR. When the SD distance increases, the PER of the DR deteriorates.

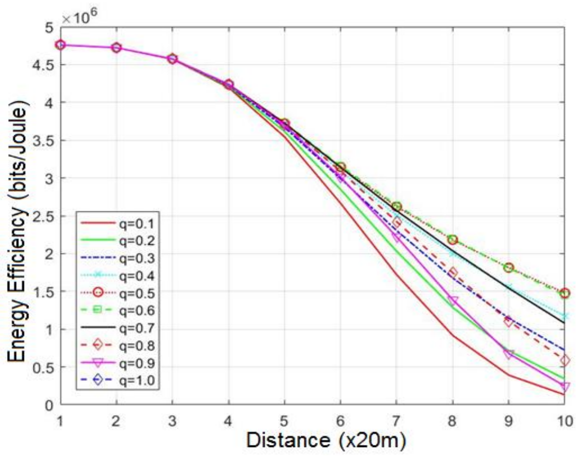


Fig. 2 EE at different relay positions

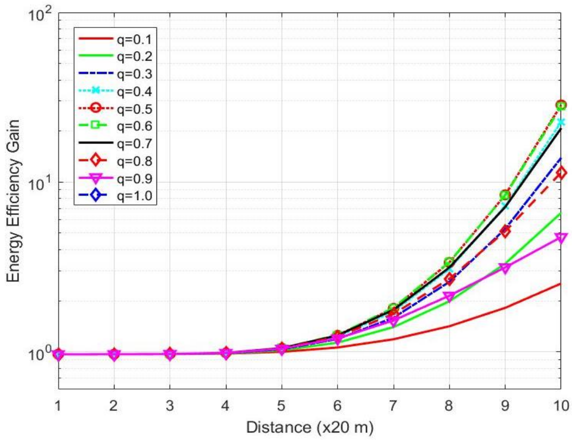
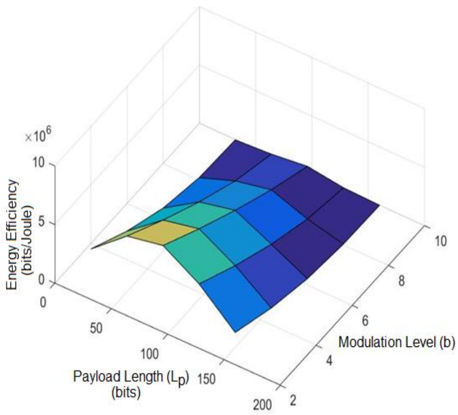


Fig. 3 EEG at different relay positions

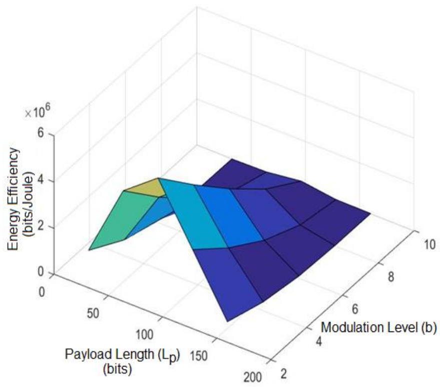
When the SR distance is equal to the RD distance (q=0.5), the EEG is best at all of the relay positions. When the SD distance is less than 100 m, the relay location effectively doesn't affect the EEG.

4.2. Impacts of the Payload Length and Modulation Level on EE

The effects of payload length and the modulation level on EE of CR at r_{sd}=140 m and r_{sd} = 160 m are plotted in Fig. 4.



(a) r_{sd} =140 m



(b) r_{sd} = 160 m

Fig. 4 Variation of EE

It can be seen from Fig. 4 that the EE depends on payload length, and the level of modulation. Smooth EE plane in Fig. 4, shows the flat EE. EE depends on payload length, and the level of modulation. As flat EE is shown in Fig. 4 at r_{sd} = 140 m. Then, q=0.7 is chosen in section 5 for optimization of EEG using PSO, RGA algorithms.

5. OPTIMIZATION OF EEG IN WIRELESS SENSOR NETWORKS

In this section, the EEG is optimized using two optimization techniques: PSO and RGA. Where distances between nodes in WSN, modulation level and payload length are the variable parameters in optimizations. The GA is an evolutionary optimization technique and a stochastic method, searching global minimum by following the principles of genetics and natural selection. GA deals simultaneously with a large number of variables for global optimization. The RGA works with real-valued continuous variables to optimize the cost function, though the algorithm follows the same features of genetic recombination and natural selection [25]. Different operator or parameter values should be RGA adjusted. A group of genes of random values (0 to 1) form the chromosomes, and the initial population is created by a set of chromosomes [26]. Cost of each chromosome is evaluated from this population and the best-valued chromosomes are used for natural selection process and rests are discarded. Offsprings are created from these selected parent chromosomes. The weight 'h' is calculated using a random number 'r' and cross-over operator 'μ' as [25, 26]

$$h = (2r)^{1/(1+\mu)} \qquad if\, r > 0.5 \tag{14}$$
$$= [(1/2(1-r)]^{1/(1+\mu)} \qquad otherwise$$

New Offsprings are:

$$Offspring1 = [(1 + h)parent_1 + (1 - h)parent_2]/2$$
$$Offspring2 = [(1 - h)parent_1 + (1 + h)parent_2]/2 \tag{15}$$

Some randomly selected chromosomes are used for the mutation with mutation operator 'η' and mutation weight 'p', where,

$$p = (2r)^{\frac{1}{1+\eta}} - 1 \qquad if\, r \leq 0.5 \tag{16}$$
$$= 1 - [2(1-r)]^{1/(1+\eta)} \qquad otherwise$$

The PSO algorithm or search technique, another type of evolutionary algorithm, is used to find the best settings or parameters required to maximize a desired objective [27, 28]. In PSO, each single solution in the search space of an objective function is known as a bird or particle, and the set of random particles is the initial swarm. The particles can evaluate their actual positions or fitness using the optimization functions. Randomly generated solutions (swarms) propagate in the design space towards the optimal solution over a number of iterations. The velocity of each particle is updated by its own best position solution which is particle best (*pbest*) and the best value that is tracked by the particle swarm optimizer, obtained till now by any particle is global best (*gbest*). The swarm will converge towards optimal positions by updating its information after each iteration. Each particle has a position vector $x_i(t)$ and velocity vector $v_i(t)$. Individual knowledge of a particle pbest, its own best-so-far position, and social knowledge *gbest* is the *pbest* value in swarm. In PSO the velocity update equation is [27]

$$v_i(t+1) = w * v_i(t) + c_1 * rand * [pbest - x_i(t)] + c_2 * rand * [gbest - x_i(t)] \tag{17}$$

and the position update equation is

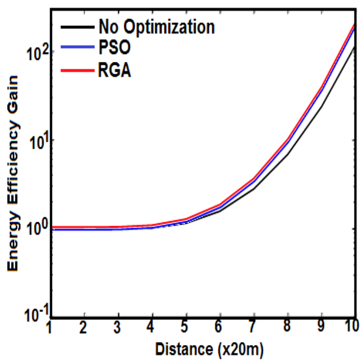
$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{18}$$

where, i - number of iterations, v_i - particle velocity at ith iteration, x_i - current particle position or solution, w - inertia weight factor, a random number between (0,1), c_1 - cognitive parameter and c_2 - social parameter, generally, $c_1 + c_2 = 4$. The particle updates its velocity and positions using the above stated procedures at every iteration to obtain the best solution.

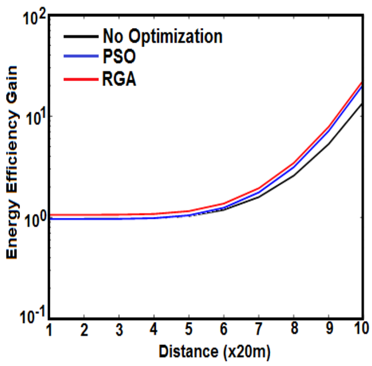
RGA works with continuous real-valued variables to optimize the cost function through genetic recombination and natural selection. After mutation has taken place, the fitness is evaluated. Then the old generation is replaced completely or partially. The different steps to implement the RGA for EE and EEG optimization are as follows. Step-1: Initialization of variables, like, distance between the nodes, level of modulation, packet length. Then lower and upper bounds of these parameters are defined along with population size, no of generations and mutation rate. Step-2: Calculate fitness using objective function (7). Step-3: Process of selection, and arithmetic cross over, mutation, and calculation of temporary fitness. Step-4: Repeat Step 3 until the population has converged. Step 5: Select the best fitness value where cost function of (7) is minimum to get maximum EEG according to (13). The different steps for the implementation of MATLAB code for PSO optimization for EE are as follows. Step-1: Initialization of PSO variables, like, population size, number of iterations, inertia weight, personal and global learning coefficients and velocity limits. Step-2: Random initialization of particle position and velocity. Step-3: Calculate fitness using objective function of (7) for each particle for personal and global best solution. Step-4: Update position and velocity of each particle using (17) and (18) and repeat step 3, 4 until the population has converged. Step-5: Select the global best solution where cost function (7) is minimum to get maximum EEG according to (13).

The EE of DR, given by (7) is the cost function for PSO and RGA optimization. The goal is to minimize the cost function of (7) which will result in the maximization of EEG, according to (13). Both in PSO and RGA, the population size is 20 and the number of iterations is 300 and the distance varied from 20 m to 200 m, modulation level varied from 4 to128, packet length is varied from 40 to 120 bits, mutation rate is 0.1. The optimized results for EE using PSO and RGA are compared with the results without any optimization in Table 1.

The PSO and RGA optimized results for EEG for different modulations (M-QAM) M=16 and M=32 and for q=0.7 are compared with the results for without optimization in Fig. 5.



(a) M=16



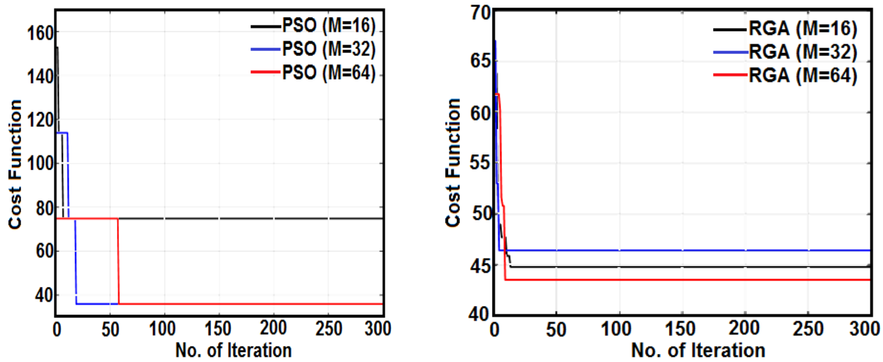
(b) M=32

Fig. 5 EEG vs. source to destination distance

Table 1 Performance comparison of optimization methods for EE

M value for M-QAM	SD Distance (x20 m)	EE without Optimization (Mbit/J)	EE using PSO (Mbit/J)	EE using RGA (Mbit/J)
M=16	6	12.55	13.81	15.59
	7	10.26	11.29	12.75
	8	8.145	8.959	10.11
	9	6.161	6.777	7.65
	10	4.307	4.738	5.348
M=32	6	12.93	14.23	16.06
	7	9.865	10.85	12.25
	8	7.022	7.724	8.719
	9	4.429	4.871	5.499
	10	2.321	2.553	2.882
M=64	6	12.02	13.22	14.93
	7	8.077	8.885	10.03
	8	4.573	5.03	5.678
	9	1.979	2.177	2.457
	10	0.61	0.671	0.758

The cost function values for PSO optimization and RGA optimization for different values of 'M' for a M-QAM modulation scheme are plotted in Fig. 6. Number of iterations used both for PSO and RGA optimization is 300.



(a) PSO (b) RGA

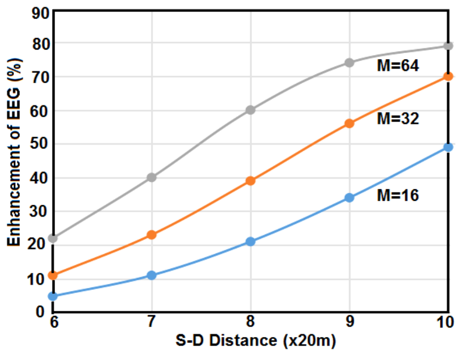
Fig. 6 Cost function for PSO and RGA optimization

The comparison of results is tabulated in Table 2. The results in Table 2 for analytical method, PSO and RGA optimization are based on the parameters [24] described above.

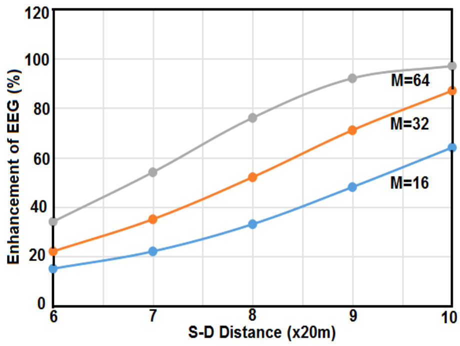
Table 2 Performance comparison of optimization methods for EEG

M value for M-QAM	SD Distance (x20 m)	EEG Without Optimization	EEG using PSO	EEG enhancement by PSO	EEG using RGA	EEG enhancement by RGA
M=16	6	1.189	1.246	4.8%	1.37	15%
	7	1.587	1.765	11%	1.941	22%
	8	2.584	3.133	21%	3.447	33%
	9	5.306	7.133	34%	7.846	48%
	10	13.89	20.73	49%	22.8	64%
M=32	6	1.565	1.735	11%	1.909	22%
	7	2.789	3.423	23%	3.765	35%
	8	6.845	9.484	39%	10.43	52%
	9	23.71	36.91	56%	40.6	71%
	10	117	199	70%	219	87%
M=64	6	2.684	3.275	22%	3.603	34%
	7	7.719	10.84	40%	11.92	54%
	8	36.44	58.25	60%	64.07	76%
	9	313.2	545	74%	600	92%
	10	7019	12580	79%	13840	97%

According to the table above, EEG using PSO for M-QAM improves from 4.8% to 49% for M = 16, 11% to 70% for M = 32, and 22% to 79% for M = 64 when compared to EEG obtained without optimization. Similarly, the improvements of EEG using RGA is from 15% to 64% for M=16, 22% to 87% for M=32 and 34% to 97% for M=64 for the minimum and maximum distances between the source and the destination compared to EEG obtained without optimization. The percentage enhancements of EEGs, obtained by optimization methods using PSO and RGA, are compared with the EEG obtained without using optimization and are shown in Fig. 7.



(a) PSO



(b) RGA

Fig. 7 Percentage enhancement of EEG using PSO and RGA optimizations

The optimized results for EE using PSO and RGA are compared with the published results in [14], [29] and [30] in Fig. 8. In [29], energy harvesting technology is used in cooperative communication using battery power in relay system. In [30], energy efficient relaying heterogeneous cooperative communication is proposed for radio access network.

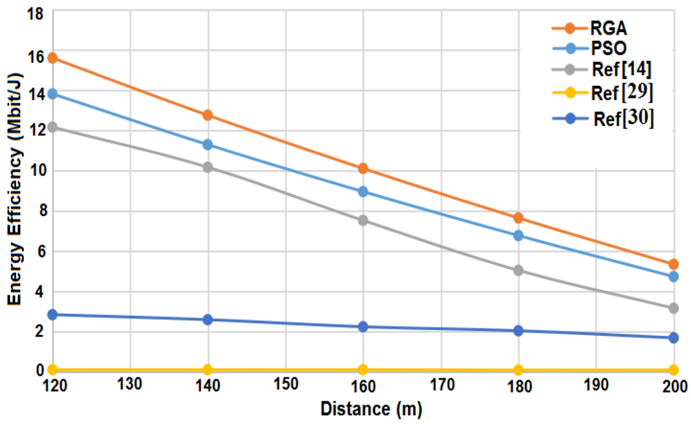


Fig. 8 Comparison of optimized EE with published results

From Fig. 8, it is evident that the optimized results using PSO and RGA show better results for EE.

6. Conclusion

Optimization of EE for a three-node incremental relaying cooperative system in a wireless sensor network is presented in this paper. Results obtained by the analytical method are compared with the optimized results using PSO and RGA. The distance is varied up to 200m and the profile of EEG is estimated. Up to a distance of 100m between the source and the destination, there is not a big deviation between analytical results and optimized results. The effects of packet size, modulation level (for M-QAM modulation) and distance on EE are simulated. Both PSO and RGA optimization results are better than the analytical method for EEG for distances greater than 100m. But the highest EEG is achieved using RGA optimization. Also the comparison of the previously published results shows that the optimization methods provide better energy efficient cooperative communication. The limitation of this work lies in the fact that only three nodes are used in this work, and in future, this work will be extended to a large number of sensor nodes.

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