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Improved energy efficiency using meta-heuristic approach for energy harvesting enabled IoT network

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Abstract

Energy scarcity is a major problem for resource constrained Internet of Things (IoT) devices. Nowadays, Energy Harvesting (EH) has emerged as a promising solution to prolong the network lifetime using radio signals in wireless relay networks. In this article, we propose an optimization algorithm, based on meta-heuristic, to enhance the energy efficiency of amplify and forward relay IoT networks. Energy constraint relay exploits power-splitting based relay protocol to acquire energy from the source and transfer information to destination. We derive an expression for energy efficiency of the system using the throughput at destination and outage probability for performance evaluation. This investigation studies energy efficiency of the network against the various system parameters which are relay location, power-splitting factor, power transmitted, data rate, energy conversion efficiency and noise power and it enables us to find out which parameters need to be optimized. Further, an objective function is formulated to achieve the optimal solution for power transmitted by the source and an adaptive particle swarm optimization (OPA-APSO) algorithm is proposed to attain maximized energy efficiency. OPA-APSO differs from most existing approaches as it provides the best amount of energy harvested while optimizing the energy efficiency. Finally, simulation results demonstrate that OPA-APSO improves energy efficiency and throughput of the network significantly as compared to other existing techniques.

Keywords: Energy harvesting; internet of things; meta-heuristic; relaying protocol; wireless energy.

1. Introduction

In the past few years, a new trend Internet of Things (IoT) has evolved in the wireless communication area. IoT represents a 3A idea according to which any media can be connected anytime anywhere (Srivastava, 2006). IoT has become very popular in the information industry due to its applications in each and every aspect of life e.g. Figure 1.

To meet these numerous applications, billions of devices are required to be connected which are battery powered with limited life-time. Recharging and supplanting batteries can improve the device lifetime, but it can be costly and risky when devices are deployed in unfavorable conditions e.g., health, military applications, etc. To address this limited power battery problem in IoT, Energy Harvesting (EH) has become very popular in research areas and is a promising solution for power limited environments (Do *et al.*, 2017; Yan and Liu, 2017; Rekha and Garg, 2018).

EH enabled relay based IoT networks is very captivating in studies, as in (Lv *et al.*, 2018; Omoniwa *et al.*, 2018; Rauniyar *et al.*, 2019; Ashraf *et al.*, 2021). Transmitting simultaneous wireless information and power transfer (SWIPT) is not a new concept. Dual use of RF signals was first highlighted by (Varshney, 2008). To take advantage of SWIPT, (Zhou *et al.*, 2013) proposed two architectures, time-switch and power-split, for the relay nodes.

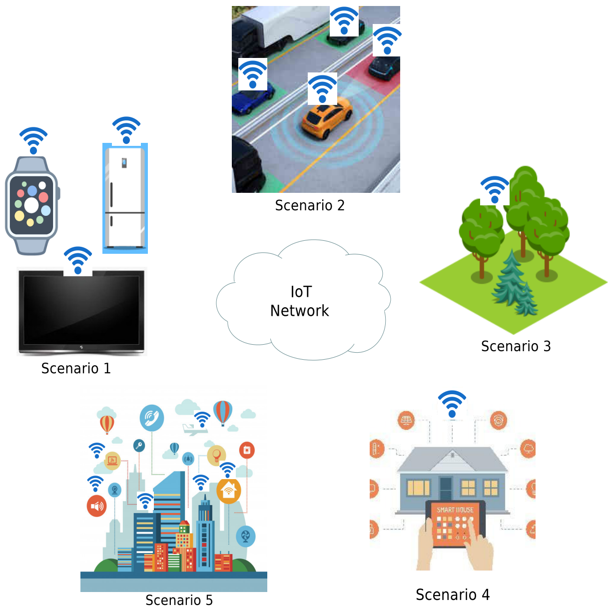

Fig. 1. IoT Scenario

(Chen *et al.*, 2014) studied the impact of power-splitting factor in dual-hop cooperative relaying system for the SWIPT scheme and evaluated the outage probability and ergodic capacity of the system. For the same relaying system, (Shah *et al.*, 2016) investigated the throughput of dual-hop cooperative relaying system by introducing a SWIPT scheme and analytical results described that at higher transmission rate (Shah *et al.*, 2016) outperformed (Chen *et al.*, 2014). Further, (Huang *et al.*, 2018) studied another network, in which both relay and direct branches can be used for transmission, but only a single branch is active at a time. In this, authors evaluated the performance of switch and stay technique using outage probability. In addition to this, (Yan *et al.*, 2018) introduced a framework for RF energy harvesting in relay based underlay cognitive networks. In this paper, prime focus was on energy harvesting using the SWIPT approach.

Further, the impact of energy harvested by the relay on outage probability and throughput was investigated in (Do, 2015). Authors proposed a scheme for an energy harvesting cooperative network and evaluated it using monte-carlo method. Later, authors introduced a dynamic allocation scheme exploiting PSR protocol for AF relaying network in (Do, 2019) and the monte-carlo method was used for analysis. Also, (Zou *et al.*, 2019) introduced PS based EH enabled optimal relay selection approaches in IoT network. (Nasir *et al.*, 2013) analyzed dual-hop AF system relay system (using both TSR and PSR) for optimal throughput using numerical analysis. Later, (Nasir *et al.*, 2014) examined throughput and ergodic capacity of EH enabled relay network by employing TSR and PSR protocols. Results showed PSR outperforms TSR protocols at a wide range of SNR, small relay distance etc.

Also, there are research works in literature which aim to optimize their objective to improve the performance of EH-enabled relaying networks. (Tang *et al.*, 2018) proposed an optimization algorithm to solve optimal power allocation problem for wireless acoustic relay sensor networks and analyzed the throughput of the system. (Rauniyar *et al.*, 2018) developed an algorithm to maximize sum-throughput using the Golden section search method and evaluated it in a PS based IoT relay system.

In addition to this, (Gurjar *et al.*, 2018), analyze the impact of SNR and target rate on throughput and energy efficiency of EH enabled IoT communication system. It can be inferred from the results that the energy efficiency depends on SNR value. Further, (Ji *et al.*, 2018) focused on energy efficiency of IoT network exploiting the PS relaying scheme. For this situation, the authors formulated an optimization problem to focus on energy management and solved this using the Lagrangian multiplier method. Also, (Lv *et al.*, 2018) introduced the iterative optimization algorithm employing Lagrange multipliers to maximize the energy efficiency of an IoT network.

As mentioned above, the majority of the existing studies mainly deal with outage probability and throughput of the system. The techniques in literature attain the optimal value of throughput/energy efficiency using numerical analysis or analytical analysis without considering the amount of energy harvested by the relay.

1.1 Contributions

Here, we propose a meta-heuristic algorithm for energy efficiency optimization in EH-enabled IoT networks to reduce time and mathematical formulation complexity. Algorithm optimizes the energy efficiency as well as gives the best value of the amount of energy harvested by relay for that particular value of energy efficiency. To the best of our knowledge, this is the first work to study energy efficiency of a system against various parameters and to propose a meta-heuristic based optimization scheme. Main contribution of this article is listed as below:

1. Considering the dual-hop AF relay network, we present the single expression for energy efficiency of the network in delay-limited transmission mode. For achievable energy efficiency, first we obtain the outage probability, and then we evaluate throughput at the destination.
2. To gain insights, we analyze the impact of various system parameters Power transmitted (P_s), energy conversion efficiency (η), power-splitting factor (ρ_h), Transmission Rate (R), relay location and noise variances on achievable energy efficiency.
3. Further, based on this analysis, we propose a meta-heuristic based OPA-APSO algorithm to optimize the energy efficiency of a system constrained to signal-to-noise ratio. In addition to optimized energy efficiency, the proposed algorithm provides the best value of the amount of energy harvested corresponding to the achieved energy efficiency.
4. Results demonstrate significant improvement in throughput and energy efficiency compared to existing approaches. Further, statistical analysis has been carried out to evaluate the performance of the proposed algorithm.

Nomenclature: Various types of symbols used throughout this article and their meanings are given in Table 1.

1.2 Organization

Organization of remaining paper is as follows. Section 2, gives the description network model with its assumptions and information processing and energy harvesting process in detail. This Section also presents mathematical expressions for system's throughput and energy efficiency. Following this, the optimization problem is formulated in Section 3. To solve this formulated problem, Section 4 explains OPA-APSO algorithm in detail. Section 5 demonstrates obtained results and a comparison with existing approaches. Finally, we summarize the paper in Section 6.

Table 1. Nomenclature

Parameters	Meaning	Parameters	Meaning
P_s	Power transmitted by source	n_r^a	additive white Gaussian noise (AWGN) at relay node
T	Time Block	n_r^c	additive conversion noise at relay
η	RF to power conversion efficiency	n_d^a	additive white Gaussian noise at destination
s_i	Transmitted signal	n_d^c	additive conversion noise at destination
ρ_h	Power splitting factor	P	Power received by relay
d_{sr}	Distance between source and relay	$\mathbb{E}_h$	Energy harvested by relay
d_{rd}	Distance between relay and destination	P_{out}	Outage Probability
m	Path loss exponent	$\mathbb{SNR}_d$	Signal-to-noise ratio at destination
R	transmission Rate	EE	Energy Efficiency of system
h and g	Channel gain between source and relay and between relay and destination	γ_{thr}	minimum value of SNR at destination node

Note: In the article symbol $\mathbb{S}$ represents the signal. Symbols r/s/d in subscript represent whether signal is at relay, source or destination.
Symbols rec/tra in superscript of $\mathbb{S}$ represent whether signal is transmitted or received.

2. Network model and description

In this article, we consider a scenario as presented in Figure 2 for AF IoT relay network. This system consists of 3 nodes, featuring a single antenna for each node. In this dual-hop communication system, source (S) transmits wireless information to destination (D) via relay node. There is no direct communication between S and D, and communication takes place through R only. Relay node is power restrained. First, R acquires energy using a signal received from S and then uses the energy to amplify and forward the data to D. Channel gain coefficients from S to R and R to D are denoted by h and g respectively. For this system, quasi-static block fading channels are assumed which are independent and remain fixed over one time block.

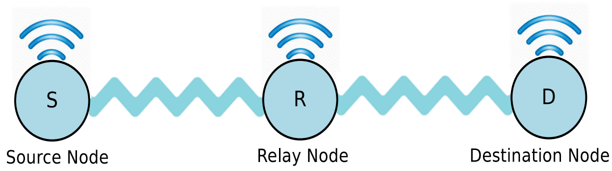

Fig. 2. System Model

2.1 Energy harvesting and information processing in PSR based IoT network

Figure 3 depicts the transmission block diagram according to PSR(Nasir *et al.*, 2014) for wireless information and energy transmission. In this protocol, the total time block (T) is partitioned into two slots. During the first slot, T/2, communication takes place by transferring data from source to relay. In the second slot, the relay node communicates with the destination. Relay harvests the energy along with information processing in the first time slot. Relay harvests the energy by using a fraction (ρ_h) of power received (P), i.e ($\rho_h P$), and the rest of received power, i.e ($(1-\rho_h)P$), is for data processing.

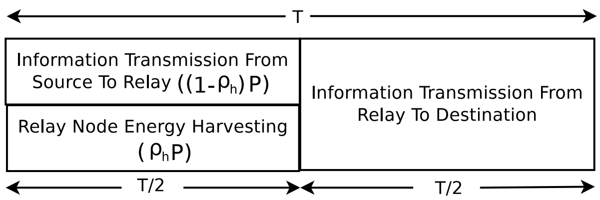

Fig. 3. PSR protocol illustration

Relay scavenges the energy first in the energy harvesting phase which is consumed in the transmission phase. Energy harvested by relay depends on both power received by relay and time duration of harvesting phase. Relay scavenges the energy for $T/2$ time period. So, harvested energy by relay ($\mathbb{E}_h$) is

$$\mathbb{E}_h = \frac{\eta \rho_h P_s |h|^2}{d_{sr}^m} T/2, \tag{1}$$

where, η is between 0 and 1 and its value depends on the circuitry (Shaikh and Zeadally, 2016). Signal received by relay is not the same as transmitted by source. Hence, after adding the noise signal n_r^a by the receiver at relay, signal received at relay $\mathbb{S}_r^{rec}$ is

$$\mathbb{S}_r^{rec} = \frac{\sqrt{P_s(1-\rho_h)} h s_i}{\sqrt{d_{sr}^m}} + (1-\rho_h) n_r^a, \tag{2}$$

where s_i is signal transmitted with unit power, h$\sim$ $\mathbb{CN}$(0,1) is channel gain between source and relay.

Relay processes $\mathbb{S}_r^{rec}$ by converting it from RF to baseband. During the conversion, additive noise n_r^c is added to the signal due to conversion. So, $\hat{\mathbb{S}}_r^{rec}$, signal obtained after the down conversion at relay node, is given as

$$\hat{\mathbb{S}}_r^{rec} = \frac{\sqrt{P_s(1-\rho_h)}hs_i}{\sqrt{d_{sr}^m}} + (1-\rho_h)n_r^a + n_r^c, \tag{3}$$

Before retransmitting the received signal, it is amplified at the relay node. Hence, relay transmits information $\mathbb{S}_r^{tra}$ which is as follows

$$\mathbb{S}_r^{tra} = \frac{\sqrt{\mathbb{P}_r}\hat{\mathbb{S}}_r^{rec}}{\sqrt{\frac{(1-\rho_h)P_s|h|^2}{d_{sr}^m} + (1-\rho_h)(\sigma_r^a)^2 + (\sigma_r^c)^2}}, \tag{4}$$

where, $\mathbb{P}_r$ is transmitted power to destination by the relay. $\mathbb{P}_r$ can also be calculated as

$$\mathbb{P}_r = \frac{\mathbb{E}_h}{T/2} = \frac{\eta P_s|h|^2\rho_h}{d_{sr}^m}, \tag{5}$$

T/2 is the total duration during which communication takes place between relay and destination. Denominator in eq.(4) represents the power constraint factor at the relay node. By replacing the variance of n_r^a and n_r^c with $n_r \triangleq \sqrt{(1-\rho_h)}n_r^a + n_r^c$, combined variance $\sigma_r^2 \triangleq (1-\rho_h)(\sigma_r^a)^2 + (\sigma_r^c)^2$, eq.(4) can be expressed as

$$\mathbb{S}_r^{tra} = \frac{\sqrt{\mathbb{P}_r}\hat{\mathbb{S}}_r^{rec}}{\sqrt{\frac{(1-\rho_h)P_s|h|^2}{d_{sr}^m} + (\sigma_r)^2}}. \tag{6}$$

Destination node receives signal $\mathbb{S}_d^{rec}$ which can be given as

$$\mathbb{S}_d^{rec} = \frac{g\mathbb{S}_r^{tra}}{\sqrt{d_{rd}^m}} + n_d^a + n_d^c, \tag{7}$$

Using eq.(3),(5) and (6), signal received at destination in eq.(7) can be simplified as

$$\mathbb{S}_d^{rec} = \underbrace{\frac{\sqrt{\eta\rho_h(1-\rho_h)}P_s gh^2 s_i}{\sqrt{d_{rd}^m d_{sr}^m}\sqrt{(1-\rho_h)P_s|h|^2 + d_{sr}^m(\sigma_r)^2}}}_{\text{Signal Part}} + \underbrace{\frac{\sqrt{\eta\rho_h P_s}ghn_r}{\sqrt{d_{rd}^m}\sqrt{(1-\rho_h)P_s|h|^2 + d_{sr}^m(\sigma_r)^2}}}_{\text{Noise Part}} + n_d, \tag{8}$$

where $n_d \triangleq n_d^a + n_d^c$ is combined AWGNs at destination. $\mathbb{S}_d^{rec}$ in eq.(8) consists of two parts, i.e., signal part and noise part. Hence, the signal-to-noise ratio ($\mathbb{SNR}_d$), i.e. $\frac{\mathbb{E}\{\text{Signal Part}^2\}}{\mathbb{E}\{\text{Noise Part}^2\}}$ at node D can be expressed as eq.(9).

$$\mathbb{SNR}_d = \frac{\eta\rho_h(1-\rho_h)P_s^2 g^2 h^4}{\eta\rho_h P_s g^2 h^2 d_{sr}^m(\sigma_r)^2 + P_s|h|^2 d_{sr}^m d_{rd}^m(1-\rho_h)(\sigma_d)^2 + (d_{sr}^m)^2 d_{rd}^m(\sigma_r)^2(\sigma_d)^2} \tag{9}$$

Throughput: This article considers delay limited transmission mode where throughput of the system is analyzed by calculating outage probability (P_{out}) for a particular data rate (R bits/sec/Hz) and $R \triangleq \log_2(1+\gamma_{thr})$, where γ_{thr} is threshold SNR, i.e $\gamma_{thr} = 2^R - 1$, for which destination can correctly detect the data. The P_{out} can be determined as

$$\mathsf{P}_{out} = \mathsf{Pr}(\mathbb{SNR}_d < \gamma_{thr}) \tag{10}$$

The outage probability of destination for the protocol is given by the following proposition(Nasir *et al.*, 2013).

Proposition 1: For PSR protocol, outage probability at destination D can be determined as

$$\mathsf{P}_{out} = 1 - \frac{1}{M_h}\int_{k=\frac{z}{y}}^{\infty} e^{-\left(\frac{k}{M_h}+\frac{wk+x}{(yk^2-zk)M_g}\right)} dk \tag{11}$$

$$\mathsf{P}_{out} \approx 1 - e^{-\frac{z}{yM_h}}\beta\mathcal{K}_1(\beta) \tag{12}$$

For convenience, we have defined

$$w = P_s d_{sr}^m d_{rd}^m \sigma_d^2 (1-\rho_h)\gamma_{thr},$$
$$x = d_{sr}^{2m} d_{rd}^m \sigma_r^2 \sigma_d^2 \gamma_{thr},$$
$$y = \eta\rho_h(1-\rho_h)P_s^2,$$
$$z = \eta\rho_h P_s d_{sr}^m \sigma_r^2 \gamma_{thr},$$
$$\beta = \sqrt{\frac{4w}{yM_hM_g}},$$

here, M_h and M_g represent means for the exponential random variables $|h|^2$ and $|g|^2$ respectively. And $\mathcal{K}_1(.)$ denotes first order modified Bessel function of the second kind(Gradshteyn and Ryzhik, 2014). Detailed derivation of this proposition is given in (Nasir *et al.*, 2013)[1]. Here, effective communication time is $T/2$, hence throughput at destination is give as:

$$THR = \frac{(1-\mathsf{P}_{out})RT}{2T} = \frac{R(1-\mathsf{P}_{out})}{2} \tag{13}$$

Energy Efficiency: Energy efficiency of a system is characterized as a ratio of spectrum efficiency of a system over the whole power consumption of an IoT network. Here, total power expenditure is represented as $aP_s + b$ as in (Ji *et al.*, 2018). $a > 1$ and $b > 0$ are factors considering power conversion efficiency and the hardware circuits in the power consumption model. Thus, using eq.(13), we present energy efficiency at node D here, which can be determined as given below

$$EE = \frac{THR}{aP_s+b} = \frac{R(1-\mathsf{P}_{out})}{2(aP_s+b)} \tag{14}$$

3. Problem formulation

To enhance the energy efficiency of the system, this section deals with the first step of optimization i.e. optimization problem formulation to attain the optimal value of P_s. Here, we formulate our objective function to maximize the energy efficiency of the system subjected to constraint to minimum SNR at destination as follows:

$$\begin{gathered}\underset{P_s}{Max}\, EE\left(P_s\right), \\ \text{s.t. } \mathbb{SNR}_d \geq \gamma_{thr}\end{gathered} \tag{15}$$

Here, $EE\left(P_s\right)$ represents energy efficiency as a function of power transmitted by source. Further, formulated objective function can be given as by inserting eq.(14) into eq.(15):

$$\begin{aligned}&\underset{P_s}{Max}\frac{(1-\mathsf{P}_{out})R}{2(aP_s+b)} \\ &\text{s.t.} \frac{\eta\rho_h(1-\rho_h)P_s^2g^2h^4}{\eta\rho_hP_sg^2h^2d_{sr}^m(\sigma_r)^2+P_s|h|^2d_{sr}^md_{rd}^m(1-\rho_h)(\sigma_d)^2+(d_{sr}^m)^2d_{rd}^m(\sigma_r)^2(\sigma_d)^2} \geq \gamma_{thr}\end{aligned} \tag{16}$$

The optimization problem represented by eq.(16) is a non-linear constraint problem. Also, complex computational terms involved in computing outage probability need to be solved iteratively with low implementation and time complexity. Therefore, we proposed an OPA-APSO algorithm to attain the optimal solution.

[1]Detailed proof is provided in (Nasir *et al.*, 2013) and omitted here due to the space limitation.

4. Proposed algorithm

This section introduces a novel optimization algorithm OPA-APSO to maximize the energy efficiency of a system. OPA-APSO optimizes system parameters to maximize the achievable energy efficiency. Further, the proposed algorithm has an extra characteristic that it keeps track of the amount of energy harvested while maximizing the energy efficiency. OPA-APSO uses a meta-heuristic approach to give the finest energy efficiency for the considered IoT network. To solve the intractable optimization problem, meta-heuristics techniques are very impressive in the research area (Mortazavi and Ahmadi, 2019; Rao *et al.*, 2020; Gupta *et al.*, 2021; Devi and Prabakaran, 2021). There is no doubt that this field will continue to develop in the near future in the studies (Dokeroglu *et al.*, 2019). Also, opposite to exact methods which require high computational time to find the optimal solution, meta-heuristic techniques attain near optimal solution rather quickly (Hussain *et al.*, 2019).

(Poli *et al.*, 2007) introduced a meta heuristic approach inspired by the social behaviour of birds and fishes known as "Particle Swarm Optimization (PSO)". Many optimization problems have been solved successfully using PSO. PSO has the ability to explore the global space and exploit local space. PSO is very robust and also converges to optima very fast. Also, PSO has been used in a large and various real life applications. So, we opt the PSO for energy efficiency optimization. To get better results, we make it adaptive by varying the inertia weight. Using the time-varying inertia weight, premature convergence and local optima is avoided.

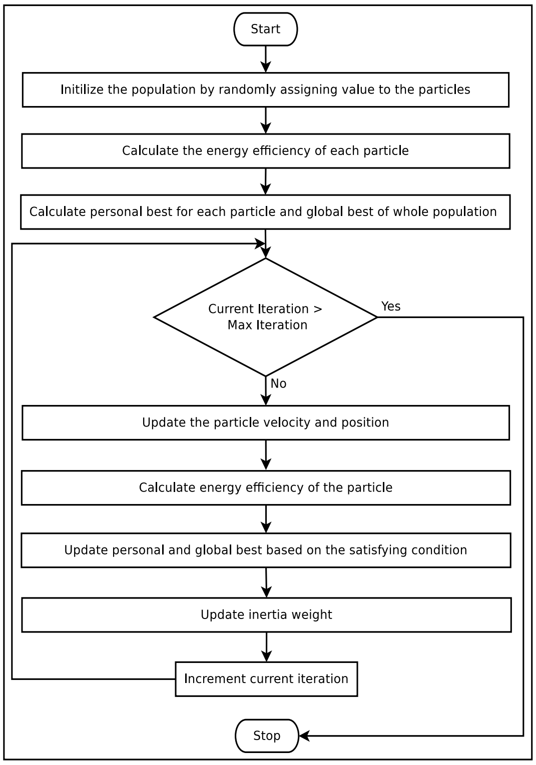

Fig. 4. Flowchart of OPA-APSO

Here, we present the Optimal Power Allocation algorithm using Adaptive PSO (OPA-APSO) to solve the optimization problem formulated in eq.(16). Flow chart of the proposed scheme is shown in Figure 4. Here, the algorithm is explained in detail.

Algorithm 1 is divided into two sections: Initialization and Updation. In the initialization section , all the algorithm parameters are initialized and in the updation section, values are updated to find the optimal result.

4.1 Initialization

Algorithm 1 : Optimal Power Allocation algorithm using Adaptive PSO
Procedure OPA-APSO

1: *Initialize the nPop, MaxIt, c1, c2, wMax, wMin, gBest=0*
2: **for** *i=1 to nPop* **do**
3:     *Initialize the positions of particles x_i by assigning random values of power transmitted by source.*
4:     *Initialize the velocity of particle v_i using random value*
5:     *Evaluate the fitness EE(x_i) using Algorithm 2*
6:     *Set the $pBest_i$ to the current position x_i*
7: **for** *i=1 to nPop* **do**
8:     **if** $EE(pBest_i) > EE(gBest)$ **then** $gBest$=$pBest_i$
9:     **if** $EE(pBest_i) = EE(gBest)$ **then**
10:         **if** $EH(pBest_i) > EH(gBest)$ **then** $gBest$=$pBest_i$
11: **for** *it=1 to MaxIt* **do**
12:     **for** *each particle x_i* **do**
13:         *Update the velocity of particle using eq.(17)*
14:         *Update new position using eq.(18)*
15:         *Evaluate the Fitness EE(x_i) using Algorithm 2*
16:         **if** *EE(x_i)>* $EE(pBest_i)$ **then** $pBest_i$=x_i
17:         **if** *EE(x_i)=* $EE(pBest_i)$ **then**
18:             **if** *EH(x_i)>* $EH(pBest_i)$ **then** $pBest$=x_i
19:         **if** $EE(pBest_i) > EE(gBest)$ **then** $gBest$=$pBest_i$
20:         **if** $EE(pBest_i) = EE(gBest)$ **then**
21:             **if** $EH(pBest_i) > EH(gBest)$ **then** $gBest$=$pBest_i$
22:     *Update inertia w=wMax-it*((wMax-wMin)/MaxIt);*
23: **return** *gBest*

From steps 1 to 8, all the parameters are initialized. In step 1, various parameters are set which are:

a. nPop: Total number of population.

b. MaxIt: Total number of iterations.

c. Learning Parameters (c1,c2): c1 is a cognitive learning parameter and represents the particle's desirability moving towards its own success. c2 is a social learning parameter and represents the particle's desirability moving towards the neighbor's success.

d. Inertia weight (w): used to control variation of velocity in the succeeding iteration from the previous one. The value of w has an impact on exploration and exploitation. Higher value of w facilitates exploration, while smaller w is beneficial for local search.

In steps 3 and 4, population vector and velocity vectors are initialized. In the population vector, each particle is assigned position x_i randomly. Velocity vector is initialized by assigning a random velocity v_i to each particle. Then calculate the fitness of particles using step 5. Assign current particle position to personal best ($pBest$) for each particle in step 6, which is the best position of particle till now. From all the personal bests, find the global best position ($gBest$) in step 7 to step 10. If EE of the personal best is greater than the global best then set $gBest$ to $pBest$ in step 8. If EE of the $pBest$ and $gBest$ are the same then their energy harvested is checked in step 9. If the EH($pBest$) is greater than the EH($gBest$) then $gBest$ is reset to $pBest$ in step 10.

4.2 Updation

In this section, values are updated to find the optimal solution.

a Velocity Update: In step 13, the velocity of each particle is updated in each iteration using personal best position and global best. The velocity is updated using eq.(17) to move the particle towards global best and its own best (Chen and Yu, 2005).

$$v_{ij} = w * v_{ij} + \underbrace{c_1 * r_1 * (pBest_i - x_{ij})}_{\text{particle personal best}} + \underbrace{c_2 * r_2 * (gBest - x_{ij})}_{\text{global best}} \quad (17)$$

Here, x_{ij} and v_{ij} are the position and velocity of i^{th} particle in j^{th} iteration respectively. r_1 and r_2 are random values between 0 and 1.

b Position Update: Using the updated velocity in step 13, the position of each particle is updated so that the particle can move towards optimal value. In step 14, a new position for each particle is obtained using eq.(18) in each iteration. As the velocity is calculated using both personal best and global best factors, the same impact will be on particle position.

$$x_{ij} = x_{ij} + v_{ij} \quad (18)$$

c Personal Best Update: Step 15 calculate the fitness value for each particle and then based on new fitness, each particle's personal best is updated. If the new fitness value is higher than the $pBest$ of the particle the $pBest$ is updated to that position in steps 16-18.

d Global Best Update: Based on the previous steps, steps 19-21 update the global best to current best position. It yields the highest fitness value among all personal bests till that iteration along with the highest energy harvested for the same energy efficiency.

e Inertia Weight Update (w): Value of w affects the ability of exploitation and exploration. We need to avoid local minima and exploit the global space. Hence, to obtain exploration $\&$ exploitation trade-off, time adaptive w is used (Shi and Eberhart, 1998). The inertia weight is calculated as:

$$w = wMax - it * ((wMax - wMin)/MaxIt), \quad (19)$$

where, $wMax$ represents initial inertia weight and $wMin$ is the final value of inertia weight. it is the current iteration.

If the number of iteration exceeds $MaxIt$ then the algorithm stops by returning the $gBest$.

Algorithm 2 : Evaluate Fitness EE(x) and Energy Harvested EH

1: *Input all the parameters* P_s,*a*,*b*,*g*,*h*,η, ρ_h, d_{sr}, d_{rd}, σ_d, σ_r
2: *Calculate* $\mathbb{SNR}_d$ *at destination using eq.(9)*
3: *Calculate outage probability* P_{out} *using eq.(12)*
4: *Calculate throughput THR of system using eq.(13)*
5: *Calculate energy harvested EH by relay using eq.(1)*
6: *Calculate energy efficiency EE of system using eq.(14)*
7: **return** *EE and EH*

Algorithm 2 describes the evaluation of fitness function. Step 1 initializes the various parameters for the system model. Using all the parameters and eq.(9), signal-to-noise ratio at destination is calculated in step 2. Then using $\mathbb{SNR}_d$ and eq.(12), step 3 calculates the outage probability which is used in step 4 to obtain the throughput. Step 5 provides the energy harvested by the relay node. Finally, in step 6 energy efficiency of the system is evaluated which is our objective function.

4.3 Computational complexity

OPA-APSO aims to maximize the system energy efficiency with the best value of energy harvested by relay. In each iteration, OPA-APSO moves towards the convergence by finding the optimal value of power transmitted. Computational complexity is analyzed under the worst case scenario, i.e, convergence is obtained after completing every iteration.

We assume that the algorithm takes *m* population size and *n* number of iterations. Step 1 initializes all the parameters with O(1) time complexity. For loop (Steps 2 to 6) runs for *m* times to calculate the $pBest$ of each particle. So, the complexity of this loop is O(*m*).

The next $pBest$ of i^{th} particle (i=1,....., *m*) is achieved by some set of operations like addition, multiplication and comparison. Hence, predicting the $pBest$ of each particle is computed in *m* computation time. Therefore, the computation time of steps 7 to 10 is O(*m*), as all the operations have O(1) time complexity. Now, each operation from steps 13 to 21 is performed for each particle in each iteration, i.e, *m* times. So, the time complexity of steps 11 to 22 is equivalent to O(*m***n*).

Hence, overall complexity of proposed OPA-APSO is O(*m*)+O(*m*)+O(*m***n*) in dual-hop relay based IoT system which is equivalent to O(*m***n*).

5. Results and analysis

Analytical results using the expressions derived in the previous section are presented here. We have obtained results into two sets using MATLAB 2016. First set is carried out to investigate the effect of system parameters on energy efficiency. This set provides how energy efficiency varies with each parameter. And based on this analysis, the second set is used to optimize the energy efficiency keeping in consideration to give the best value of energy harvested.

We compare our approach with approaches (Ji *et al.*, 2018), (Nasir *et al.*, 2013) and (Do, 2019). (Ji *et al.*, 2018) consider a dual-hop relay network system exploiting PSR protocol and optimize the energy efficiency at the destination. Authors optimize the solution by using the optimal value of the power-splitting factor. (Nasir *et al.*, 2013) study the impact of various parameters on throughput of the system for both TSR and PSR protocols and optimize the throughput. They provide the analysis which protocol performs better in which situation. Further, (Do, 2019) optimizes the throughput of relay based model using PSR. They find the optimal value of the power-splitting factor to optimize the throughput of the system. Mentioned approaches use numerical methods to solve the optimization problem.

5.1 Impact of various system parameters

In our considered system, default values for the various parameters are adopted as P_s =1 Joules/sec, η =1, m =2.7 and R =3 bits/sec/Hz. d_{sr} and d_{rd} are normalized to 1. Antenna noise covariances (σ_a^2) and conversion noise covariances (σ_c^2) at both relay and destination are assumed equal for simplicity. The mean values M_h and M_g of channel gain parameters $|h|^2$ and $|g|^2$ are assigned unit values. These simulation settings are in line with work by (Nasir *et al.*, 2013). Power consumption parameters: *a* varies from 2 to 10 and *b* = 10,100 and 300 (Ji *et al.*, 2018).

From eq.(14), it can be seen that a system's energy efficiency depends on various parameters P_s, R, η, ρ_h, d_{sr}, $d_{rd}, \sigma_c^2, \sigma_a^2$, etc. So, we study the analysis of different parameters on the system's energy efficiency individually keeping all other parameters fixed.

Figure 5 plots energy efficiency of the system vs. power transmitted by the source node for various values of power consumption parameters. From Figure 5, it is obvious that the energy efficiency increases with the increase in P_s till it reaches an optimal value and then it starts decreasing for each curve. It is due to an increase in total network power consumption (aP_s+b) with the increase in transmitted power. Throughput increases as P_s increases. For lower value of power, increase in throughput is more considerable than the total power consumption. On the other hand, increase in total power consumption is more considerable than throughput at the higher values of power. So this results in first increasing the energy efficiency of the system upto optimal value then it starts decreasing. Total power expenditure is low for the lower values of a and b, but it increases with increase in a and b. For the lower values of

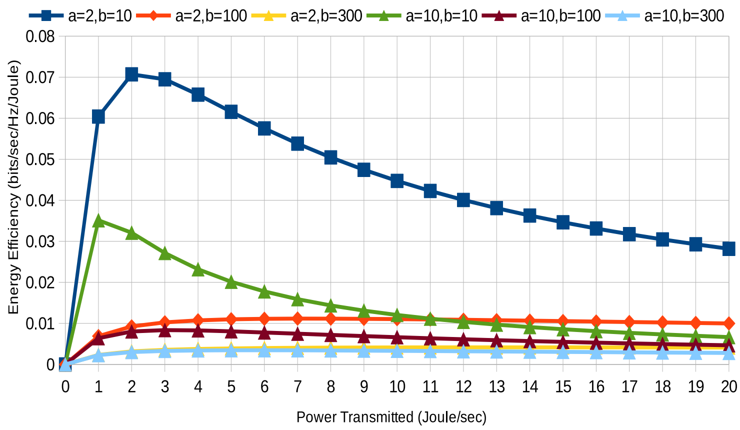

Fig. 5. Energy Efficiency vs. P_s

b, aP_s is considerable when P_s changes. It results in a significant change in energy efficiency with an increase in P_s for lower values of a and b. But due to the high value of b, change in aP_s is significantly low as compared to b with the increase of P_s. Hence, there is negligible change in energy efficiency.

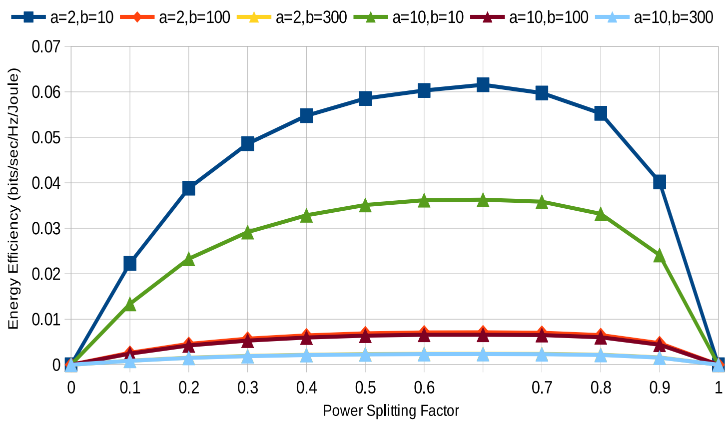

Fig. 6. Energy efficiency vs. power splitting factor (ρ_h)

Figure 6 shows achievable energy efficiency as a function of power splitting factor (ρ_h). We can see the energy efficiency of the system first increases upto some optimal point and then start decreasing as ρ_h approaches to 1 for various values of a and b as depicted in Figure 6. Reason is that for the smaller values of ρ_h relay harvests less power which yields lower energy efficiency of the system. On the contrary, for the values of ρ_h larger than the optimal value, the relay node has more power to harvest and less energy to process the information. Therefore, the relay node has low signal strength and it results in lower energy efficiency.

Further, the location of the relay (d_{sr}) between source and destination also affects the efficiency as shown in Figure 7. Here, d_{rd} is set to $d_{rd} = 2 - d_{sr}$ for all curves. As we can see from Figure 7, the system's energy efficiency decreases as d_{sr} increases. It is due to the reason that as d_{sr} increases both signal received and energy harvested by the relay decrease which results in lower energy efficiency.

Figure 8 plots the variation of energy efficiency with different values of R. Energy efficiency increases with increase in R upto optimal value and then starts decreasing as shown in Figure 8 for every curve. At lower data transmission rate energy efficiency increases with increase in data rate. Contrary to this, at higher values of R, the receiver is not able to decode a large amount of data correctly in a limited period. Therefore, there is an increase in outage probability ($\mathbb{P}_{out}$), which leads to decrease in energy efficiency.

Figure 9 plots the variation of energy efficiency with different values of energy conversion efficiency

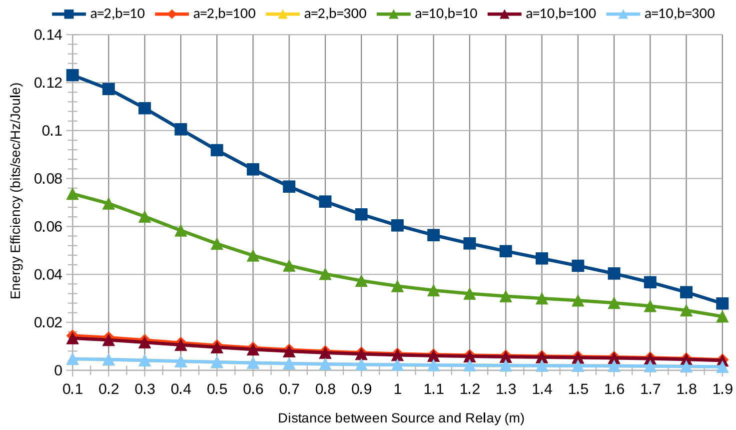

Fig. 7. Energy efficiency vs. distance between source and relay (d_{sr})

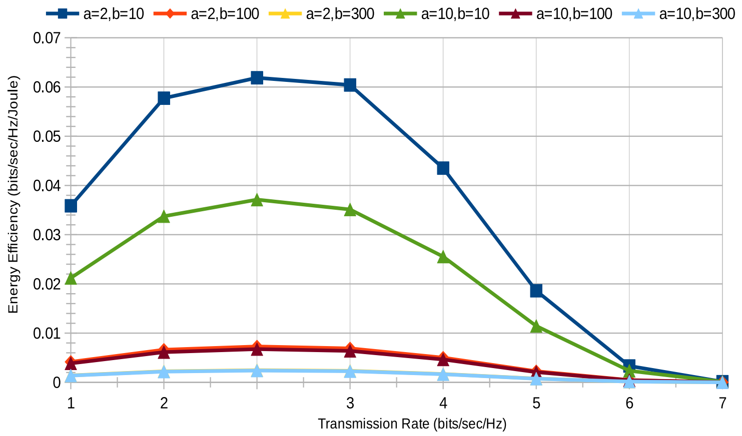

Fig. 8. Energy efficiency vs. data transmission rate (R)

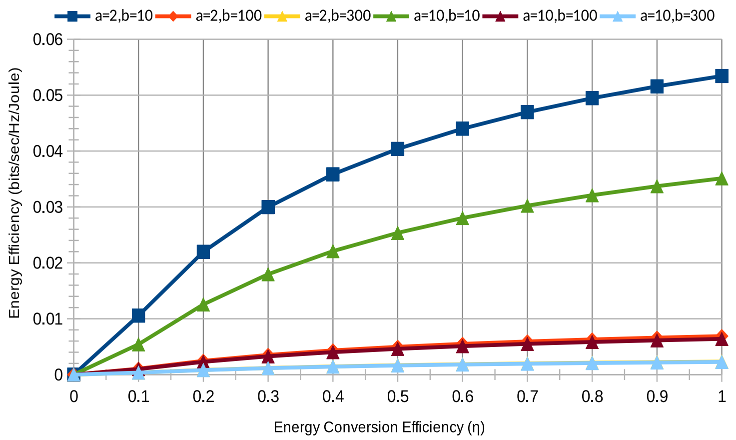

Fig. 9. Energy efficiency vs. energy conversion efficiency (η)

(η). Energy efficiency increases with increase in η.

Figure 10 depicts the effect of conversion noise variance (σ_c^2) on the energy efficiency of a system by keeping all other parameters fixed. From Figure 10, it can be observed that energy efficiency decreases with increase in σ_c^2. The increased conversion noise affects the throughput at destination which results in lowering the energy efficiency for various values of a and b. And the similar trend is followed in

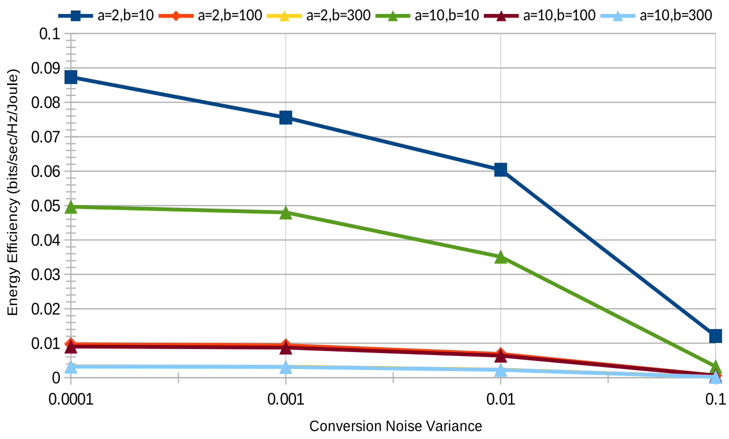

Fig. 10. Energy efficiency vs. conversion noise variance

Figure 11, which plots the variation of energy efficiency with different values of antenna noise variance (σ_a^2).

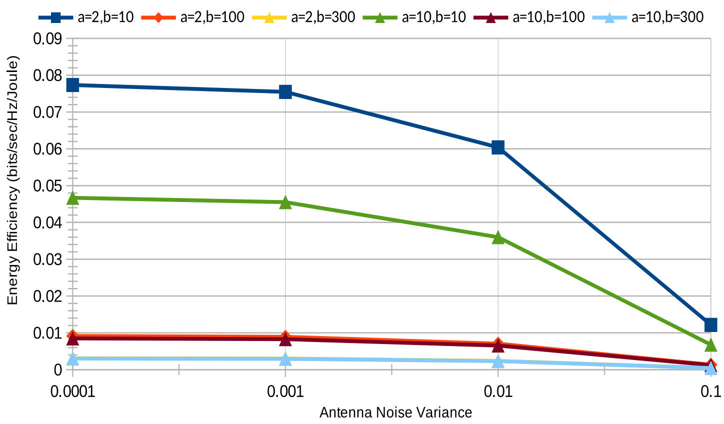

Fig. 11. Energy efficiency vs. antenna noise variance

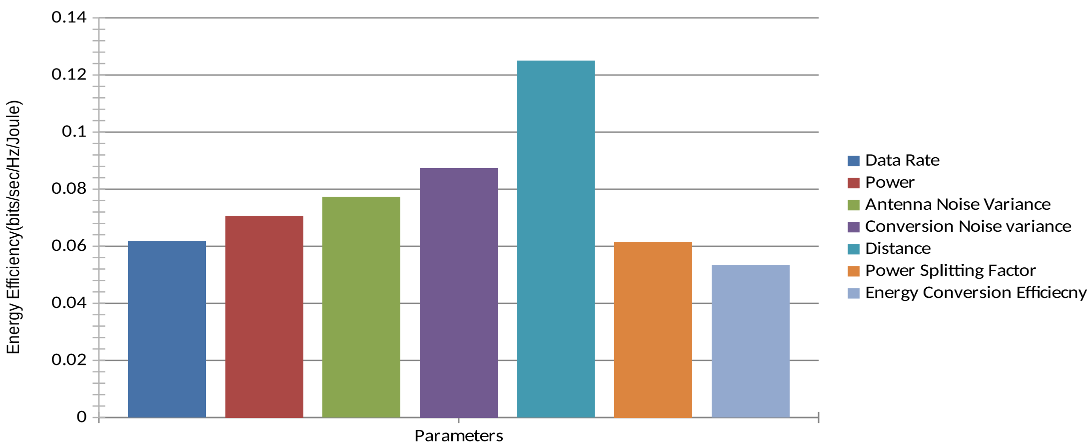

Fig. 12. Optimized Energy Efficiency for various parameters

5.2 Optimized energy efficiency using OPA-APSO

In the previous section, we analyzed how energy efficiency of system is affected by various system parameters. Energy efficiency varies linear fashion with η, d_{sr}, σ_c^2 and σ_a^2 while with P_s, ρ_h, R parameters varies in parabolic pattern. Based on this analysis, we employ the OPA-APSO to find the optimal values of power transmitted to optimize the energy efficiency. Based on this analysis, we employ the OPA-APSO to find the optimal values of system parameters to optimize the energy efficiency. OPA-APSO optimizes the energy efficiency against only one parameter at a time. We also optimize the R and ρ_h using OPA-APSO. Figure 12 represents the optimized energy efficiency of the system for the various parameters and the obtained optimal values of different system parameters $P_s, R, \eta, \rho_h, d_{sr}, \sigma_c^2, \sigma_a^2$ are 2.0468,2.6288,0.63799,1.2024E-07,0.0001,0.0001 and 1 respectively.

5.3 Statistical analysis

We run the OPA-APSO algorithm over 15 cycles and the simulation results are represented by the mean values. To evaluate the statistical performance of the proposed algorithm, we have used the standard deviation and coefficient of variance (CoV). Standard Deviation (SD) is a method used to measure the distribution of the data about the mean value. CoV% is calculated as:

$$CoV\% = \frac{SD}{Mean} * 100$$

Lower values of SD and CoV mean results provided by the algorithm are stable. Table 2 gives the values of mean, SD and CoV for various parameters.

Table 2. Statistical Analysis of Results

Parameter	Mean	SD	CoV%
Data Rate	0.061872	1.11E-05	0.018
Power	0.070682	1.24E-05	0.01756
Antenna Noise Variance	0.077338	1.51E-05	0.01954
Conversion Noise Variance	0.087339	1.48E-05	0.01689
Distance	0.125	2.23E-05	0.01782
Power Splitting Factor	0.061559	1.17E-05	0.01895
Energy Conversion Efficiency	0.053423	1.07E-05	0.01998

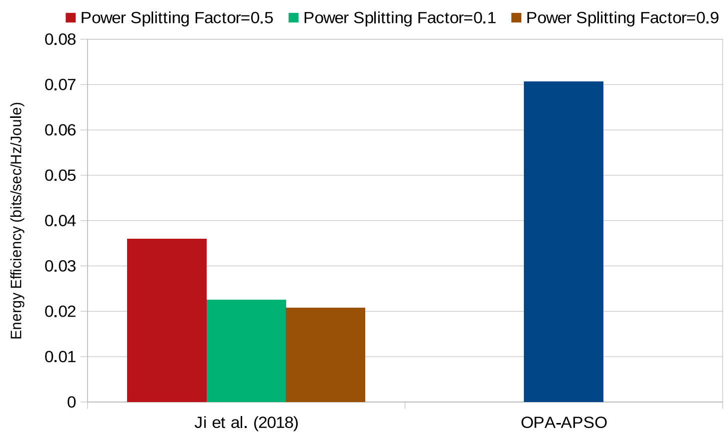

Fig. 13. Optimized Energy efficiency of OPA-APSO and (Ji *et al.*, 2018) at various ρ_h values

5.4 Comparison of OPA-APSO with existing approaches

To show the efficacy of the proposed approach, we compare OPA-APSO with already existing relaying techniques (Nasir *et al.*, 2013; Ji *et al.*, 2018; Do, 2019) for energy harvesting. Table 3 summarizes above discussed approaches w.r.t. to parameters, objective and method used to achieve optimal results.

Figure 13 shows the comparison of optimized energy efficiency between OPA-APSO and (Ji *et al.*, 2018). Optimized energy efficiency values of (Ji *et al.*, 2018) are shown for three different values of ρ_h 0.1, 0.5 and 0.9 as shown in Figure 13. OPA-APSO achieves 96% higher efficiency than (Ji *et al.*, 2018).

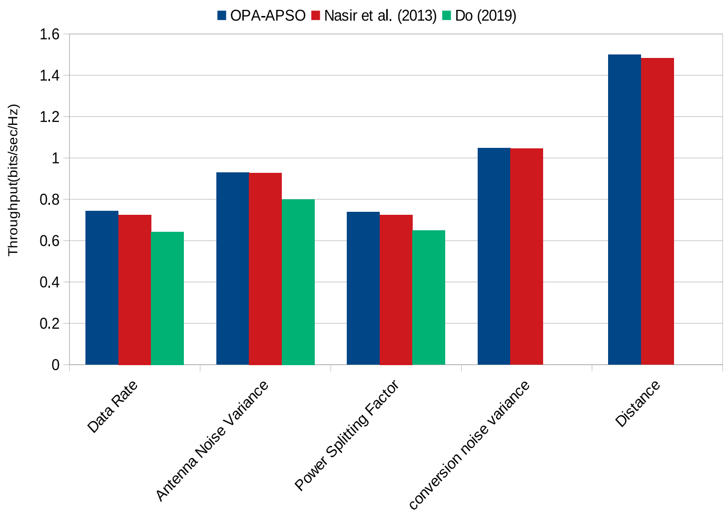

Fig. 14. Comparison of optimized throughput with existing approaches at various parameters

Figure 14 presents a comparison between throughput of the considered IoT system by using OPA-APSO and approaches used in (Do, 2019) and (Nasir *et al.*, 2013) and it is observed that OPA-APSO gives better results than these approaches for optimal value of power-splitting factor, data rate, antenna and conversion noise variance, and distance respectively. The results show that there is a considerable improvement in the throughput using the OPA-APSO algorithm to find out the optimal transmission power. Throughput is enhanced by 50% and 35% over approaches (Do, 2019) and (Nasir *et al.*, 2013) respectively.

Table 3. Comparison of proposed approach with existing approaches

Author	(Nasir *et al.*, 2013)	(Ji *et al.*, 2018)	(Do, 2019)	**OPA-APSO**
System	Dual-Hop	Dual-Hop	Dual-Hop	Dual-Hop
Type	Amplify-and-Forward	Amplify-and-Forward	Amplify-and-Forward	Amplify-and-Forward
Technique	Numerical Analysis	Lagrangian multiplier method	Monte Carlo Method	Adaptive PSO
Objective	Throughput	Energy Efficiency	Throughput	Energy Efficiency
Parameter	Power-Splitting Factor	Transmitted Power	Power-Splitting Factor	Transmitted Power
Throughput	0.724	-	0.65	**0.98955**
Energy Efficiency	No	0.036	No	**0.070682**
Considering Amount of Energy Harvested	No	No	No	**Yes**

6. Conclusions and future directions

In this article, we have studied the EH enabled cooperative communication network for IoT devices. Relay employs PSR to harvest the energy and process the information in the amplify-and-forward IoT network. Our main motive is to optimize the system's energy efficiency. For this, we present the expressions for the outage probability and energy efficiency for delay limited transmission mode under quasi-static block fading. Also, we investigate the impact of $P_s, R, \eta, \rho_h, d_{sr}, d_{rd}, \sigma_c^2, \sigma_a^2$ on energy efficiency individually. Numerical results reveal how these parameters affect energy efficiency and drive us to optimize the parameters to obtain the maximized energy efficiency. Further, we formulate the optimization problem for achievable energy efficiency at the destination, simultaneously considering the amount of energy harvested by the relay. In order to solve the optimization problem, we have proposed a meta-heuristic based OPA-APSO algorithm to achieve the maximized energy efficiency. The proposed approach also gives the best value of the amount of harvested energy by the relay node for the achieved energy efficiency. Results show the efficacy of OPA-APSO over the existing schemes. Further, statistical analysis is performed which shows the stability of the algorithm. In the future, it would be interesting to optimize other important factors along with energy efficiency as multi-objective optimization problem.

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