Optimal Energy-Delay Scheduling using Improved Beetle Antennae Search (BAS) for Energy-Harvesting WSNs

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Abstract

Optimal energy delay scheduling for capacity allocation issues on interference channel energy harvesting wireless sensor networks (EH-WSN) addresses for static data streams and energy topography. To create the optimizations issue of unique and multi-time interval correspondingly. The goal is for reducing overall regression of the network. Though, the optimization issue is not convex, creating it hard to get an optimal solution. The main objective of this manuscript is directly addressing the original non-convex formulation using the enhanced Beetle Antennae Search (BAS) algorithm that efficiently finds the optimal solution. This algorithm is also better for another complex optimization issues on wireless network design. The simulations under delay, delratio, drop, energy, network lifetime, overhead and throughput are carried; the expected outcome displays that improved BAS algorithm executes considerably better than the convex approximation technique. This idea is useful for other complex optimization issues on wireless network design.

1 Introduction

EHWSN are extensively used on several areas like environmental monitoring, smart building, remote monitoring, smart cities and smart transportation because of its low cost, self-sustain ability and simple operation. Therefore, it newly attracted a lot of attention on IoT and wireless networks. In meantime, the capacity allocation issue Gul and Demirekler (2018) is a crucial problem to design EH-WSN. It is a usual scenario wherever sensor nodes are organized on extremely two-dimensional (2D) region of interest. Every sensor node periodically gathers the sensed data and sends it to receiver in multiple hops Yousaf et al. (2017).

The problem of capacity allocation on EH-WSN with interference channel is often not concentrated and hard for solving directly. For realizing a joint optimization solution, the earlier operation studied the static data flow model using concentric approximation technique of single interval Wang et al. (2016). Though, the convex approximation technique is only suitable for high SINR. This is often unsatisfactory for actual world EH-WSNs while close data links obstruct through everyone a lot. Furthermore, traditional techniques Song and Zheng (2018) tend to adopt more complex or slower integration mechanisms. This motivates to contemplate the best technique for tackling a demanding issue and to accomplish best network performance. Evolution algorithms (EAs) are widely applied on numerous fields and superior performance have been shown to be effective for complex optimization issues. Liu et al. (2017). Currently, EAs also create numerous applications on WSNs for addressing complex computing issues posed by large-scale networks or large-volumes of data. Though, the applications are aimed at using EA to address traditional issues like location, routing, clustering, QoS and topographic control Lanza-Gutierrez and Gomez-Pulido (2015).

Beetle Antenna Search (BAS) as promising EAs displays best performance for multimodal and non-concentrated optimization issues on real-world applications. It takes completely unique perspective,
which BAS potential algorithm is frequently evolved for tackling as network optimization challenging issue in restriction conditions Li et al. (2017) Based on this paper, the event is split into, within initial part; the flow of information on every electric circuit is assumed to be fixed, when the flow of energy is variable. Every sensor node collects energy only once during an interval. Initially, the optimization issue for single interval and multiple time intervals, correspondingly. After that propose a constrained BAS, i.e., EDS-BAS, for optimizing information rates; power allocations and power transfer, thereby reducing network lag. Specifically, the penalty function method Kwan and Fapojuwo (2017) is employed to address restriction conditions within the EDS-BAS optimization process.

The major contributions of this manuscript are below:

- Non-convex capacity allocation issue on EH-WSNs through interference channel is due to improved BAS algorithm.
- For static data streams and obtainable energy on EH-WSNs through data interference channel, first assume capacity allocation issue in single and multiple time intervals, correspondingly.
- Create an optimization issue for multiple time interval and discover that it may be solved by studying their characteristics on every time slot.
- To transform the constrained optimization problems (i.e. the objective function) in the unrestrained optimization issues (minimizing the objective function) via outside penalty function system.

Use Modified Energy-Delay Scheduling (EDS), a promising improved BAS algorithm to achieve optimal power allotment, power transfer and minimal network delay

The expected outcome displays that improved BAS algorithm executes considerably better than convex approximation technique.

Remaining manuscript is mentioned as below. Section II describes the related work. Section III describes the preliminaries. Section IV describes proposed method on EH-WSNs for static data flows and improved Beetle Antenna Search algorithm. Section V explains the experimental outcomes. At last, Section VI concludes this manuscript

2. Literature Review

In 2019, Sarkar, et al Sarkar and Murugan (2019) have introduced a cluster-head approach for effectual transmission of knowledge through less energy. Firefly algorithm was established to exploit the energy competence of network and lifetime of nodes by optimally choosing cluster header. Time delay was directly proportionate with distance among nodes as well as base stations. Sensor nodes were choosen in the simplest way to accommodate the station under the cluster head. Therefore, time delay may be significantly decreased. Thus, the turn will increase the transmission speed of the information packets. Based on this manuscript, firefly through cyclic randomization was used to choose the most efficient cluster head. Running and combining the cluster-based topology together with grid-based may be a big
problem, especially for hierarchical route. Additionally, capacity, performance, end-to-end delay, security, real-time delay, and conflict were some of the demands that multi-target route supports.

In 2019, Vieeralingaam, et al Vieeralingaam et al. (2020) have introduced the problem of interference and distortion reduction as optimization issue on energy-harvesting WSNs by resource allotment restrictions. This matter was first presented because there is a doublet of the ratios in non-concentric problem. Then convert a problem that is considered to be a differential amount of problem. Moreover, a solution was acquired using innovative Newton's technique. Numerical simulations are carried out for established approach and parameters investigated contain the variance of the error and the energy obtainable for harvesting. Outcomes confirm an efficiency of suggested approach still channel estimation errors.

In 2019, Jiao, et al Jiao et al. (2019a) have introduced the difficulty of capacity allocation within wireless sensor networks (WSN) of energy harvesting by interference channels. For fixed information and energy topologies, the optimization issue was formulated while the flow of information leftovers stable on entire data connection and every sensor node collects energy during the interval; optimal solution properties are attained through Lagrange duality using CVX solver to solve the problem.

In 2018, Cao et al Cao et al. (2018) have suggested that combined planning and power control on wireless network, flow assignment, connection programming and power control for wireless network capabilities. To introduce a mechanism based on machine learning combined by support vector machine as well as optimistic neurological network for tackling with optimization issue. Though there are few EAs depends on power control and capacity allocation issues, only certain operation focus on capacity allocation issue on EH-WSN through interruption channel.

In 2019, Tao, et al Tao et al. (2019) have introduced the efficient algorithms to dynamically program MS to collect data from sensors through dissimilar data generation rates. This manuscript introduced an optimization structure that has three stages. The primaries cater to the allocation of reliable, stable and neutral energy for sensors. After that get a closed path of MS for sensory data collection, which involves a lot of aggregation nodes that determines the rate at which every sensor generates information and data flow of every connection that improves network performance.

In 2018, Xu et al Xu et al. (2018) have introduced the secure allocation energy-harvesting cognitive radio sensor networks (EHCRSN) resources based on tiny low-cell network, in which for adaptive or static transfer power for cooperative interference When choosing a cell base station or cell phone users and choose the arbitrary pair. Channels go behind the fading of block (i.e., the channel positions do not change based on every transmission of block, but may change from one module to another) and each CS independently undergoes the fading of the channel, in which a fading of the block coincides with one frame.

In 2018, Koufoudakis, et al Koufoudakis et al. (2018) have introduced an innovative version of Probabilistic Flooding, known as Robust Probabilistic Flooding that was able to perform through battery nodes preparing to run out resume its operation subsequent to harvesting environmental energy. The
Mark off chain is additionally introduced for capturing the behavior of energy harvesting evaluated and simplified for deriving analytic expressions with respect to the probability that a node was an operational or inoperative state as charging or discharging state.

In 2013 Fauladgar et al. Jahani et al. (2019) have found the problem of optimization of simultaneous flows of information and energy in communication networks based on graphics with energy transfer. Although they research the issue of optimizing the joint transmission of information and the transfer of energy, they disregard the interference between the data links. To solve optimum power programming for distributed sensing on Gaussian sensor networks of independent and associated clarification. For balancing collective user usage, entire network cost, power control, rate allotment, routing and congestion control are collectively optimized on wireless networks.

3 Preliminaries

Network model and problem formulation

Assume EH-WSNs in which N sensor nodes are placed approximately and seamlessly at given area. It explained through direct graph \( G = (V, E) \) in which \( V = \{ \text{among sensor nodes, Jiao et al. (2020) i.e.,} \ (\in E, \) only if a node \( v \) may transmit a message with node \( v \) in power restriction \( p_{ij} \). Data collection tree \( T = (19\text{by sink } V_0 \text{on root node. This implies acyclic expansion sub graph } G = (V, E) \text{ in which } V_T = V \text{ and } E_T \subseteq E. \) On data collection tree \( T \), sensor nodes \( v, v' \) is siblings it consists of similar parent. Every sensor node \( V_n \) sometimes transmit the direction data toward \( V_0 \) ossemi-dual mode. Emay be transfer as sensor node i to j through the energy link \( q, q \in 1 \ldots Q \), while the sensor node j needs energy to function

1Communication model:

Assume the physical interference model between EH-WSN based on real data link tree. The data connection delay \( l \) goes behind M / M / 1 queue model and assume time interval is great sufficient. Similarly Aoudia et al. (2017), it may be characterized as (1)

Where \( d_l \) implies amount of data flow, \( c_l \) implies communication link data rate \( l \) where \( d_l \leq c_l, \forall l \in E_T. \) For \( \forall l \in E_T, \) let transfer force of \( l. \) To utilizep = \{of entire real link in every time intervalSINR received from data link \( l \) is(2)

Where \( tt_{ll} \) indicates the channel gain as transmitter \( l \) to receiver \( l. \) It depends on several factors like path loss, shading and fading influences. Zhang et al. (2016) Mainly, \( tt_{ll} \) implies data link \( l \) gain and \( \sigma_{ll} \) is data link arrives noise power \( l. \)

According to Shannon's formula data rate and data link may be obtained as (3)
For each sensor node \( n \), total power exhausted in data connection \( l \) and the power connection \( q \) is fulfilled with exploitable energy (4)

Here indicates sensor node \( x_q \) implies in energy link \( q \). Consider \( K \) and \( B \) be connection connection correspondingly \( E \) restriction be rewritten as (5)

**Capacity Assignment Problem in EH-WSNs with Interference Channel**

For static data streams and obtainable energy on interference channel EH-WSNs, assume the problem of capacity allocation in unique and multiple time interval, correspondingly.

*Case of Single Time Slot:*

For a single energy harvest on every time interval, total delay in the EH-WSN through interference channel \( D_t \), (6)

The objective to reduce the total delay on network, (7) s.t. (8)

Where the SINR constraint that (8) guarantees the data link receiver \( l \) may be correctly decode.

To utilize the data rates on equation (3), optimization issue may be provided, (9) (10) (11)

For adopting EH-WSN half duplex, the optimization problem (9) may be assumed \( l \) real data links on network at every time interval separately, (12) (13) (15)

*Case of Multiple Time Slots:*

This section, energy arrival rates of every sensor terminal may modify over time. Assume that time is drilled, every time interval consists of similar length. Every sensor node \( n \) may collect \( E_{nt} \) units at every time interval \( t \), here \( t = 1 \ldots T \) and \( T \) implies entire time intervals at data collection. Variables \( d_{lt}, c_{lt}, p_{lt}, \sigma_{lt} \) and \( x_{qt} \) state data flow, data rate, power, as well as energy transmission on time interval \( t \), correspondingly.

Consider the data flow \( d_{lt} \), channel gain \( t_{lt} \), channel noise power \( \sigma_{lt} \) does not modify \( t \) at intervals denoting \( d_{lt} = d_l \), channel gain \( \forall \forall \) [22] For ensuring the M/M/1 approximation allocation issue on every time interval is sensible consider that every time interval is adequately greater to average delay. Therefore equation (1) rephrase iin time interval \( t \) (16)

Where (17)

The energy collected in the time interval \( t \) may be utilized while the energy is reached. Thus, energetic causality of every sensor node \( n \) on time may explained (18)
For static data streams on interference channel EH-WSNs, the capacity allocation issue for reducing entire delay on entire data collection may be provided as, \((19) (20) (21) (22)\)

Energy transfer occur i.e., \(x_{qt} \geq 0\)

The optimization problem \((18)\) becomes \((23)(24)(25)\)

Optimization problems are non-optimization issues as intention functions as well as restriction conditions are not concentrated regarding to transmit power \(p\). Therefore, it can be hard to get worldwide optimum solutions using convex approximation method. Masood et al. (2018) Improved and promising BAS algorithm modified energy delay scheduling (EDS) for attaining optimum power allotment, power transmission and minimal network delay

\textit{Algorithm}

\begin{algorithm}
\begin{algorithmic}
\State \textbf{while} \(t < t_{\text{end}}\) \textbf{do}
\State Initialize the parameters of the improved BAS, i.e., \(\lambda, d_s, l_{\text{step}}, x, x_{lbest}\) and \(x_{rbest}\)
\State Calculate the fitness of \(x, x_{lbest}\) and \(x_{rbest}\) and initialize \(J_{P lbest}, J_{P \text{best}}\) and \(J_{P \text{rbest}}\)
\For {\(i = 1\) to \(N\)}
\State Calculate minimal network delay \(\varphi(p, r)\).
\State Verify the \(I\) th better Power Allotment vector: \(p^{\ast}i \leftarrow \text{arg min}\)
\State I Record the best power allocation vector: \(p^{\ast}i \leftarrow \text{arg min in optimal power allocation.}\)
\EndFor
\State Set \(t \leftarrow 0\)
\State \textbf{while} \(t \leq T_{\text{max}}\) \textbf{do}
\State Set \(\lambda_t \leftarrow N(1, 0.1 - 0.1 \ast\)
\For {\(i = 1\) to \(N\)}
\State \textbf{while} (maximum iteration is not reached) or (stop criterion) \textbf{do}
\State Generate the direction vector unit \(d\) search invariable space with two antennas according to, Eqn (14)
\For {each antenna} \textbf{do}
\State \EndFor
\EndFor
\EndWhile
\EndAlgorithm
\end{algorithm
Use the states $X_s(t)$ and $X_T(t)$ and the antenna $x_l$ or $x_r$ to calculate the future risks $F_{CRi}(t)$ in prediction horizon accordingly.

Calculate the objective function value of antenna Update to the local optimal values of two antennas end for

Update end while Make

end for end if end while

4 Proposed Method

Optimal energy delay scheduling using improved Beetle Antenna Search

Since it's hard to get a worldwide optimum solution of optimization issue, propose a numerical technique interms of BAS algorithm to get the near-optimum power allotment, power trans- mission, as well as minimal network delays. The Beetle Antenna Search Algorithm (BAS) is extremely capable optimization system proposed on 2017. Compared to Particle Swarm Opti- mization (PSO) search algorithm, only single individual is required at BAS.

**Exterior Penalty Operational Approach for Restricted Optimization:**

Because BAS does not apply straightly to restricted optimization issues, it initially converts restricted optimization issues into unconstrained optimization issues by outer penalty function technique.

Consider the optimization issue is((

Here $f_0$ implies object function, i.e., minimal network delay. The function $f_i, i = 1, .., m$, implies constrained function. P denotes power allotment vector. Next, outer penalty function for optimization issue may be denoted,(

Here $r$ implies optimistic penalty parameter, $q$ implies non-negative constraint and $m$ implies number of restriction condition.

**Optimization process of Beetle Antenna Search:**

To achieve optimal power allotment, power transmission and minimum network delay, BAS improved Energy Delay Scheduling (EDS) algorithm. EDS-BAS is provided that executes the BAS for optimization issues.

EDS-BAS contains the following steps,
The parameters to optimize are control sequence \( N_p \). (29)

Two \( N_p \)-dimensional vectors left and right antenna of beetle implies \( x_l \) and \( x_r \) correspondingly. To utilize and \( d_s \) denotes the centroid of beetle as well as distance. Then the preliminary values of \( \delta_p \) allocate in the direction of centroid, compute the preliminary cost value and consider it recent minimal cost \( J_p \text{min} \).

Consider the beetle antennae direction is arbitrary that may be indicated via random vector \( \text{dir} = (N_p, 1) \) as right to left antenna. After compute through \( \text{dir} \) normalization is

Assume the direction of the beetle antenna is random, which can be represented by the random vector \( \text{dir} = (N_p, 1) \) from the right antenna to the left antenna. Dir normalization after calculating two antennas(30) where, \( d_s \) can be considered to the probing step of two antennas. Select \( x_l \) or \( x_r \) correspondingly depend on Eq. (30) for multi-step control imitation on forecast horizon, as well as gather motion data.(31)

While the beetle centroid is upgraded, select to control imitation and recomputed cost insimilar time. Next compare to current minimal cost to upgrade the optimum parameters \( x_{\text{best}} \) and minimal cost operational value by greedy strategy:(32)

At this point, BAS search iteration completes. Implement steps 2–4 in a loop till the end of the iterations or while the minimal cost satisfies the requirement.

For adopting the initial value of \( x_{\text{best}} \) as the input to control horizon, i.e., \( () = x_{\text{best}}(1) \), and redo step 1–5 till last part of collision prevention.

**Improved BAS algorithm for constrained problem:**

Though the BAS algorithm is very short on search approach, PSO is a standard optimization technique that does not change the optimization object, although it needs less computation cost. As cost of computing the sample maximizes, the concurrent performance of search method decreases. Thus, reasonable initialization and parameter update approach may enhance search performance. If the step size \( l_{\text{step}} \) modify, two antenna positions are forever restricted through present centroid location that is simple for falling in local extreme instead of single individual. Thus, local optimal levels of two antennas and equivalent optimum objective function values are entered for recovering search approach. Eq. (29) is modified as:(33)

Where \( x_{l_{\text{best}}} \) and \( x_{r_{\text{best}}} \) implies historical optimal parameters. Then, two antennas have investigated depend on Eq. (14), \( x_{l_{\text{best}}} \) and \( x_{r_{\text{best}}} \) are updated as:(34)

Where \( J_{p_{l_{\text{best}}}} \) and \( J_{p_{r_{\text{best}}}} \) implies historical optimum left and right antenna objective function values, correspondingly. In reference to approach for updating the velocity of particles on PSO, \( x_{l_{\text{best}}} \) and \( x_{r_{\text{best}}} \) are utilized to accurate the centroid position on every repetition: (35)
Where \( r_d \in (0, 1) \) implies random value, \( c_l \) and \( c_r \) implies left and right antenna learning factors, correspondingly. Generally, \( c_l \) and \( c_r \) must be demonstrated through historical optimum cost \( J_{plbest} \) and \( J_{prbest} \) on search process. If \( J_{plbest} \) is smaller than \( J_{prbest} \) is assumed to current optimum position is nearer with global optimum position, subsequently \( c_l > c_r \) must be fulfilled, and vice versa.

Furthermore, optimization issues in energy transfer are solved via EDS-BAS algorithm. It should be noted that the representation of the solution is different from earlier one because in this case energy transfer occurs. In every solution, the allotment vector is indicated on right half of solution and energy transfer vector is indicated on left half of the solution.

**EDS-BAS Computational Complexity:**

In EDS-BAS, calculation problem may be evaluated as below: For the process of initialization, it contain computational complexity \( O(N \times Lf) \) arbitrarily creating every power allotment vector \( p \) on population; computational complexity of network delay assessment is \( O(N \times Lf) \). In every repetition of EDS-BAS, creating novel solution \( O(N \times Lf) \) based on Gaussian mutation operator; analyzing network delay and bandwidth distance as \( O(N \times Lf) \) correspondingly; upgrading the search step-size of every RLS implies \( O(N \times Lf) \). Thus, EDS-BAS calculation implies \( O(T_{max} \times N \times Lf) \). As given \( T_{max} \) EDS-BAS computation complexity based on number of real links \( Lf \) and population size \( N \).

**Initialize solution:**

Here, \( N \) implies population size, every solution \( p_i \) indicates every probable power allotment vector. Solution dimension \( Lf \) indicates to series of real links on network in time interval. For 1st population, every power allotment vector \( p_i \) arbitrarily created in exploitable energy barrier state (line 1). For every power allotment vector \( p_i \), if their network delay \( \varphi(p_i, r1) \) is superior to another, while better power allotment vector \( p^* \) leftovers on Optimal Power Allocation

**Generate solution:**

At each repetition of the EDS-BAS, novel power allocation vectors were developed based on \( p_j \) i Gaussian mutation operator, which estimated the network delay \( \varphi \) as well as probability distribution for Bhattacharyya distance.

**Update solution:**

With every repetition, the search step size is upgraded for every random local search (RLS). EDS-BAS outputs optimal power allotment vector \( p^* \) and minimal network delay.
5 Experimental Results And Discussion

For evaluating performance outcomes depend on the improved Beetle Antenna Search (BAS) algorithm. EDS-BAS, the expected outcome displays that improved BAS algorithm execute extensively better than convex approximation technique. Jiao et al. (2019b) The simulations are carried out on PC by an Intel (R) Core (TM) i5 -7200U, 2.50 GHz CPU, 8GB of RAM and Windows 8. The entire simulation programs are executed inside the NS2 simulator. [2. 3] the simulation parameters for the proposed EDS-BAS algorithm are given below on Table 1

| Total Number of nodes | 100       |
|-----------------------|-----------|
| Node distribution range | 500mx500m |
| Node initial energy    | 0.89J     |
| Node communication radius | 110m     |
| SINR                  | $\geq 10$ |
| Uniform distribution   | U(0,1)    |
| Noise power           | $\sigma = 1 \times 10^{-5}$ |

Simulation phase 1: performance comparison of various algorithm:
In this section, several evaluation metrics, such as lag, performance, delivery rate, energy consumption, fairness index, and network life are analyzed. Here, the performance of the BAS algorithm was analyzed and compared to ACO algorithm by changing the number of nodes with constant data rate. In network, the variable channel request is depend on number of nodes provided.

Figure 2 shows the node vs delay for network scenario. The delay value for proposed BAS got 4.596506 values at node 20, 7.189551 values at node 40, 10.323822 values at node 60, 10.906996 values at node 80, and 10.147834 values at node 100.

In the figure, it obviously shown that the delay of the proposed algorithm BAS provides 14.75% lowers than ACO in node 20, delay of the proposed BAS algorithm provides 12.21% lower than ACO at node 40, delay for the proposed BAS algorithm provides 10.48% lower than ACO at node 60, delay for the proposed BAS algorithm provides 10.86% lower than ACO at node 80 and delay of proposed BAS algorithm provides 10.71% lower than ACO at node 100. By this our proposed BAS provides lower delay value compared with ACO.

Figure 3 show the delratio for the number of node in network scenario. The delratio value for proposed BAS got 0.82281 values at node 20, 0.72115 values at node 40, 0.623285 values at node 60, 0.610614 values at node 80 and 0.598908 values at node 100. From the figure, the delratio of the proposed
algorithm BAS provides 3.47% higher than ACO in node 20, delratio of the proposed BAS algorithm provides 7.44% higher than ACO at node 40, delratio for the proposed BAS algorithm provides 7.48% higher than ACO at node 60, delratio for the proposed BAS algorithm provides 7.71% higher than ACO at node 80 and delratio of proposed BAS algorithm provides 8.26% higher than ACO at node 100. By this our proposed BAS provides higher delratio compared with ACO.

Figure 4 show the drop for the number of node in network scenario. The drop value for proposed BAS got 2 values at node 20, 8 values at node 40, 12 values at node 60, 27 values at node 80 and 27 values at node 100. From the figure, the drop value of the proposed algorithm BAS provides 60% lowers than ACO in node 20, drop value of the proposed BAS algorithm provides 33.33% lower than ACO at node 40, drop for the proposed BAS algorithm provides 27.27% lower than ACO at node 60, drop for the proposed BAS algorithm provides 52% lower than ACO at node 80 and drop of proposed BAS algorithm provides 15.62% lower than ACO at node 100. By this our proposed BAS provides lower drop value compared with ACO.

Figure 5 show the energy for the number of node in network scenario. The energy value for proposed BAS got 7.578526 values at node 20, 7.845594 values at node 40, 7.887799 values at node 60, 7.603463 values at node 80 and 7.40053 values at node 100. From the figure, the energy of the proposed algorithm BAS provides 2.50% lowers than ACO in node 20, energy value of the proposed BAS algorithm provides 1.62% lower than ACO at node 40, energy for the proposed BAS algorithm provides 0.03% lower than ACO at node 60, energy for the proposed BAS algorithm provides 1.20% lower than ACO at node 80 and energy of proposed BAS algorithm provides 2.05% lower than ACO at node 100. By this our proposed BAS provides lower energy compared with ACO.

Figure 6 show the network lifetime in network scenario. The network life time for proposed BAS got 160 values at node 20, 88 values at node 40, 59 values at node 60, 54 values at node 80 and 52 values at node 100. From the figure, the network lifetime of the proposed algorithm BAS provides 37.93% higher than ACO in node 20, network lifetime of the proposed BAS provides 15.78% higher than ACO at node 40, network lifetime for the proposed BAS algorithm provides 40.47% higher than ACO at node 60, network lifetime for the proposed BAS algorithm provides 38.46% higher than ACO at node 80 and network lifetime of proposed BAS algorithm provides 36.84% higher than ACO at node 100. By this our proposed BAS provides higher network lifetime compared with ACO.

Figure 7 show the overhead for the number of node in network scenario. The overhead value for proposed BAS got 2819 values at node 20, 3548 values at node 40, 4118 values at node 60, 5191 values at node 80 and 6407 values at node 100. From the figure, the overhead of the proposed algorithm BAS provides 42.13% lowers than ACO in node 20, overhead value of the proposed BAS algorithm provides 50% lower than ACO at node 40, overhead for the proposed BAS algorithm provides 44.29% lower than ACO at node 60, overhead for the proposed BAS algorithm provides 44.33% lower than ACO at node 80 and overhead of proposed BAS algorithm provides 44.60% lower than ACO at node 100. By this our proposed BAS provides lower overhead compared with ACO.

Simulation phase 2: performance comparison of various CA techniques:
The comparison analysis of diverse measurements through different number of nodes is shown in following figure. Comparison of delay related to uneven nodes displays at Fig. 9. From the figure, the delay of the proposed method provides 28.60% lower than EDS-NCS, 42.92% lower than CA at node 20, delay value for proposed EDA-BAS provides 26.01% lower than EDS-NCS, 37.86% lower than CA at node 40, delay value for proposed EDS-BAS provides 21.40% lower than EDS-NCS, 0.31% lower than CA at node 60, delay value for proposed EDS-BAS provides 21.74% lower than EDS-NCS, 32.10% lower than CA at node 80, delay value for proposed EDS-BAS provides 21.54% lower than EDS-NCS, 33.67% lower than CA at node 100. By this our proposed EDS-BAS provides low value compared with EDS-NCS and CA.

Figure 10 displays the delivery rate of proposed technique with different rates. The delivery rate of proposed technique provides 8.88% more than EDS-NCS, 17.61% more than CA in node 20, delratio for proposed EDA-BAS provides 14.22% higher than EDS-NCS, 27.91% higher than CA at node 40, delratio for proposed EDS-BAS provides 18.89% higher than EDS-NCS, 39.19% higher than CA at node 60, delratio for proposed EDS-BAS provides 19.91% lower than EDS-NCS, 38.98% higher than CA at node 80, delratio for proposed EDS-BAS provides 20.50% higher than EDS-NCS, 42% lower than CA at node 100. By this our proposed EDS-BAS provides high value compared with EDS-NCS and CA.

Figure 11 shows the drop of the proposed technique with varying rates. From figure, the drop of proposed technique provides 80% lower than EDS-NCS, 60% lower than CA at node 20, drop value for proposed EDA-BAS provides 69.23% lower than EDS-NCS, 33.33% lower than CA at node 40, drop value for proposed EDS-BAS provides 42.85% lower than EDS-NCS, 6.66% lower than CA at node 60, drop value for proposed EDS-BAS provides 81.81% lower than EDS-NCS, 33.33% lower than CA at node 80, drop value for proposed EDS-BAS provides 61.42% lower than EDS-NCS, 47.05% lower than CA at node 100. By this our proposed EDS-BAS provides low value compared with EDS-NCS and CA.

From the Fig. 12, the energy consumption of the proposed method provides 23.87% lower than EDS-NCS, 42.31% lower than CA at node 20, energy consumption for proposed EDA-BAS provides 22.32% lower than EDS-NCS, 40.75% lower than CA at node 40, energy consumption for proposed EDS-BAS provides 21.76% lower than EDS-NCS, 40.45% lower than CA at node 60, energy consumption for proposed EDS-BAS provides 22.57% lower than EDS-NCS, 41.51% lower than CA at node 80, energy consumption for proposed EDS-BAS provides 23.46% lower than EDS-NCS, 41.82% lower than CA at node 100. By this our proposed EDS-BAS provides low value compared with EDS-NCS and CA.

Figure 13 shows the network lifetime of the proposed technique with varying rates. The network lifetime of proposed technique provides 92.77% greater than EDS-NCS, 201.88% higher than CA at node 20, network lifetime for proposed EDA-BAS provides 91.30% higher than EDS-NCS, 203.44% higher than CA at node 40, network lifetime for proposed EDS-BAS provides 96.66% higher than EDS-NCS, 210.52% higher than CA at node 60, network lifetime for proposed EDS-BAS provides 92.85% lower than EDS-NCS, 200% higher than CA at node 80, network lifetime for proposed EDS-BAS provides 92.59% higher than EDS-NCS, 205.88% lower than CA at node 100. By this our proposed EDS-BAS provides high value compared with EDS-NCS and CA.
From the Fig. 14, the overhead of the proposed method provides 31.19% lower than EDS-NCS, 15.14% lower than CA at node 20, overhead for proposed EDA-BAS provides 34.33% lower than EDS-NCS, 21.86% lower than CA at node 40, overhead for proposed EDS-BAS provides 37% lower than EDS-NCS, 28.37% lower than CA at node 60, overhead for proposed EDS-BAS provides 34.45% lower than EDS-NCS, 28.17% lower than CA at node 80, overhead for proposed EDS-BAS provides 37.78% lower than EDS-NCS, 29.68% lower than CA at node 100. By this our proposed EDS-BAS provides low value compared with EDS-NCS and CA.

Figure 15 demonstrates the throughput of improved BAS technique with varying rates. The throughput of the proposed technique provides 49.83% superior than EDS-NCS, 99.61% higher than CA at node 20, throughput for proposed EDA-BAS provides 50.04% higher than EDS-NCS, 99.92% higher than CA at node 40, throughput for proposed EDS-BAS provides 49.81% higher than EDS-NCS, 99.37% higher than CA at node 60, throughput for proposed EDS-BAS provides 50.02% lower than EDS-NCS, 99.68% higher than CA at node 80, throughput for proposed EDS-BAS provides 49.96% higher than EDS-NCS, 99.71% lower than CA at node 100. By this our proposed EDS-BAS provides high value compared with EDS-NCS and CA.

6 Conclusion

This manuscript researched the optimal data rates, power allocations, and energy transfer for interference channel EH-WSNs, while setting the data size for every data connection. To create the capacity allocation issue that is subject to data rate requirements. For fixed data streams and obtainable power on interference channel EH-WSNs, initially assume the difficulty of capacity allocation on h single and multiple time intervals, correspondingly. The capacity allocation, optimal data ratios, power allocation, power transfer and entire network lag are main issues in EH-WSN. To overcome these issues, propose an optimal Energy Delay Scheduling (EDS) using an improved BAS algorithm. This study evaluates the potential benefit of BAS algorithm on solving non-convex capacity assignment issues. In addition to this technique may be generalized for addressing other complicated and challenging issues, like linear and non- concentrated optimization on wireless networks. Since future work, to take on BAS algorithm for solving collective optimization of power, data allotment as well as topology discovery for EH-WSN on a large scale.

Declarations

Data availability statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Conflict of Interest

The authors declare that they have no conflict of interest.

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**Figures**

**Figure 1**

Flow chart for energy delay scheduling in improved Beetle Antenna Search
Figure 2

Evaluation metrics of node vs delay

Figure 3

Evaluations metric in delratio
Figure 4

Evaluation metrics of drop

Figure 5

Evaluation metrics in energy
Figure 6
Evaluation metric of network lifetime

Figure 7
Evaluation metrics of overhead network
Figure 8

Evaluation metric of throughput

Figure 9

Performance analysis of node vs delay
Figure 10

Performance analysis of node vs delratio

Figure 11

Performance analysis of node vs drop
**Figure 12**

Performance analysis of node vs energy

**Figure 13**

Performance analysis of network lifetime
Figure 14

Performance analysis of overhead

Figure 15

Performance analysis of throughput