Research Article

Energy Harvesting Wireless Sensor Network (Eh-Wsn) Based Modified Negatively Correlated Search Algorithm For Non-Convex Optimization Problems

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Abstract: Network resource allotment is a significant concern for designing energy harvesting wireless sensor networks (EHWSNs). So, in this manuscript, Modified Negatively Correlated Search by Harris Hawks Optimization (MNCSHHO) algorithm is proposed for EH-WSNs with interference channel to solve the Non convex problems. It also used for optimizing data rates, energy transfers, and minimizing the total network delay. Initially, it deals with the complicated nonlinear constraints and also optimizes the data rates and energy transfer. By this total network delay can be minimized. The simulations are performed using Network Simulator (NS2) to validate the performance of the proposed Modified Negatively Correlated Search by Harris Hawks Optimization (MNCSHHO) algorithm and it provide better results such as high network life time as 1.09, 2.34, high throughput as 0.65, 1.024, energy transfer as 24%, 51%, low delay as 20.29%, 42.416%, low drop as 2.34%, 3.3455% and low overhead as 40.52%, 23.4% are compared with the existing algorithms like EDS-NCS, convex approximation respectively.

Keywords: Energy Harvesting Wireless Sensor Networks (EHWSNs), Modified Negatively Correlated Search algorithm (MNCS), Harris Hawks Optimization (HHO), Non-Convex Problems, and Network delay.

1. Introduction

Wireless Sensor Networks (WSNs) plays a vital role for sustaining constant environmental monitoring, whereas sensor nodes are deployed and equipped to accumulate along with reassign data commencing on the environment to a base-station [1-2]. Therefore, Energy harvesting shows potential solution to offer self-sustainability and expand energy-limit Wireless Sensor Networks (WSNs) life time [3-4]. As a result, researchers had a lot of attention in the field of energy harvesting wireless sensor network in recent years [5]. Despite the fact that, the energy harvesting method from the natural environment and the radio frequency signals is unstable, due to various factors [6-7]. Wireless Energy Transfer (WET) as a gracious method for transferring energy from some energy-rich sensor nodes to energy-hungry sensor nodes for enhancing overall network performance [8-9].

Capacity assignment problem is an important issue for designing EH-WSNs [10]. During wireless communications broadcast, the data transmissions interfere with each other because of same frequency band, which is unavoidable [11]. By this result, it decreases the network performance. Because of these considerations, energy harvesting WSNs are investigated and contemplate on the delay minimization problem of the WSNs with interference channels [12]. Network resource allocation is a significant matter on behalf of manipulative energy harvesting wireless sensor networks (EH-WSNs) [13]. Therefore, by considering the energy transfer and power allocation for the fixed data flow, capacity assignment problem in the energy harvesting WSNs with interference channels are created as a non-convex optimization problem [14]. In order to attain an optimization solution, our existing work convex approximation method only suits for high SINR. This is unacceptable for real-world EH-WSNs when nearby data links heavily interfere with each other. Moreover, traditional methods are frequently assuming high-complexity algorithm. These motivated for considering efficient method to tackle such challenging problem and achieve better network performance [15].

In this work, initially, it is implicit that the data flow over each data link is permanent while energy flow is variable. Each sensor node harvests energy only once in a time slot. So, evolutionary algorithm based on the constrained Modified Negatively Correlated Search (MNCS) is proposed for energy delay scheduling to optimize the data rates, power allocations and energy transfer, so as to minimize the total network delay [16-18]. In particular, the penalty function approach is used to tackle the constraint conditions in the optimization process of Modified Negatively Correlated Search (MNCS) by Harris Hawks Optimization (HHO) algorithm [19-20]. The proposed Modified Negatively Correlated Search (MNCS) by Harris Hawks Optimization (HHO) algorithm for the optimal energy-delay scheduling problem are evaluated through simulations under different scenarios.

The main contributions of this manuscript are summarized as follows:

- In this manuscript, Modified Negatively Correlated Search (MNCS) by Harris Hawks Optimization (HHO) algorithm is proposed for EH-WSNs with interference channel to solve the Non convex problems.
- It also used for optimizing data rates, power allocations and energy transfers, and minimizing the total network delay.
- Initially, it deals with the complicated nonlinear constraints and optimizes the data rates, power allocations and energy transfer simultaneously, subsequently to minimize the total network delay.
- The numerical results will demonstrate the effectiveness of the proposed approach and it is implemented in Network Simulator (NS2) and then the performance metrics like total delay, packet drop, energy transfer, Network life time, overhead and throughput of the suggested approach will be evaluated.

The rest of this manuscript is organized as follow: The Literature survey is described in section 2. Section 3 is about proposed Energy Harvesting Wireless Sensor Network (EH-WSN) based on a Modified Negatively Correlated Search (MNCS) Algorithm for Non-Convex Optimization Problems, results of the proposed design is presented in section 4 and Lastly, Conclusions are presented in Section 5.

2. Literature Survey

In 2017, *Liu, J et.al* [21] have suggested optimal energy beam for energy harvesting (EH) wireless sensor networks for smart cities, where sensor nodes (SNs) initially harvest energy from a base station, along with data transmission are performed in the base station via time-division-multiple-access (TDMA) manner by using the harvested energy. For non-convex problem, they have used semi-definite relaxation (SDR) method. Simulation results showed that as the data amount is comparatively small, the energy consumed by circuit and information processing affects the system performance significantly, but for large data, the energy constraint for base node exaggerated is very limited.

In 2019, *Jiao, D et.al* [22] have suggested Optimal Energy-Delay Scheduling for Energy Harvesting WSNs via Negatively Correlated Search. Most traditional methods that approximate convex optimization problem by considering the relatively high Signal-to-Interference-plus-Noise Ratio (SINR). The advantage of this manuscript, it directly solve the original non-convex formulation by employing a powerful evolutionary algorithm, i.e., Negatively Correlated Search (NCS). But in the simulation result it not provide better result regarding network characteristics.

In 2018, *Zhan, C et.al* [23] have found that Energy-Efficient Data Collection in UAV Enabled Wireless Sensor Network. Mixed-integer non-convex optimization problem is solved by applying the successive convex optimization technique. The advantage of this manuscript achieved significant network energy saving. But it not provides better result regarding the network delay and power constraints.

In 2016, *Calvo-Fullana, M et.al* [24] have found that the Sensor Selection and Power Allocation Strategies for Energy Harvesting Wireless Sensor Networks. For computing optimal power allocation which was solved by applying joint sensor selection and power allocation technique. It has achieved EH-agnostic sensor selection strategy, a lower bound on distortion. But it not provides better results regarding the energy transfer and network delay.

In 2019, *Vieeralingaam, G et.al* [25] have utilized that the Convex Optimization Approach to Joint Interference and Distortion Minimization in Energy Harvesting Wireless Sensor Networks. The problem of interference and distortion minimization in energy harvesting wireless sensor networks with resource allocation constraints are performed by modified Newton’s method. The parameters like error variance, energy available for harvesting and channel estimation errors are achieved better results. But the resource allocation constraints like overhead, throughput, delay are not achieved better results.

In 2019, *Uhlemann, E., et.al* [26] have utilized reliable communications for energy harvesting (EH) wireless sensor network (WSN). Interference channel selection policy for the sensors links and access point links are improved the reliability of the communications, while enhancing the energy utilization. Channel selection strategy not only improves the probability of achieving sufficiently reliable communication but also enhances the energy utilization.

In 2017, *Bozorgi, S.M., et.al* [27] have developed the WSN clustering and routing methods are inefficient for EH-WSN. It has used distributed-centralized approach and multi-hop routing and considers criteria, like energy level, the amount of harvested energy and the number of neighbors in the clustering process. Simulation results showed that network stability and efficiency are improved. But it not provides better results regarding the energy transfer and network delay.

In 2020, *Liu, R et.al* [28] have utilized the robust data collection for energy-harvesting wireless sensor networks. Dynamics of renewable energy can be obtained by network planning stage for solving robust optimization (RO). The advantage of this manuscript, it provides better result regarding overhead, network lifetime, and low energy transfer and it was used for variability of renewable energy. But it not provides better results regarding the throughput and packet drop.

3. Proposed Method for Non-convex problem in EH-WSN
3.1 Network Model and Problem Formulation
In Energy harvesting wireless sensor network (EH-WSN), each sensor node has the capacity of harvest the energy and sense the data from the environment. Along with, it can able to transmit or receive data and energy during communication. So, sensor node can be used as transmitter, a relay or a receiver, which is determined by its location in EH-WSN. In Energy harvesting wireless sensor network, the sensor nodes are haphazardly positioned in certain communication area. If node X wants to transmit the data to node Y, first it needs to make data link 'D' between the sensor nodes X and Y under power limit. Similarly, if sensor node Y needs energy to work, it transfers the energy over energy link 'E', from node X to node Y.

3.1.1 Interference Channel Model
The interference channel model is a shared communication channel, mainly used for analyzing the interference in communication channels. The main aim is to minimize the total network delay and enhance the network performance in EH-WSNs with interference channel. For that, assume the transmit power P_d of data link 'd' lies in the range of (0, max P_d). Here power allocation vector for all active links in each time slot is denoted as PA. The value for PA is given by $\left(P_d \mid d \in TE\right)$, where TE is a Total Energy. The received SINR of data link d is given in the following equation (1)

$$SINR_d(PA) = \frac{G_{ddP_d}}{\sum_{d^* \neq d} G_{d^*dP_{d^*}} + \sigma_d} \tag{1}$$

Where channel gain G_{d^*d} for transmitter'd*' and receiver'd' depends on path loss, shadowing and fading factors. Similarly, the channel gain of data link d is denoted as G_{dd} and σ_d is the receiving noise power on data link d.

3.1.2 Communication Model
In communication model, delay in the data link can be calculated by the following equation (2)

$$Delay_d = \frac{f_d}{c_d - f_d} \tag{2}$$

For all data link $f_d \le c_d \in TE$, where f_d is the amount of data flow and c_d is the data rate of communication link d. The data rate c_d of data link d are taken from Shannon formula are given below the following equation (3),

$$c_d = \frac{1}{2}\log(1 + SINR_d(PA)) \tag{3}$$

For every sensor node S, the total power exhausted on transmission data link 'd' and energy link 'e' are contented by the exploitable energy are given below in the following equation (4)

$$\sum_{d \in O_f(S)} P_d \le E_S + \sum_{e \in \chi_e(S)} \eta_s \chi_s \tag{4}$$

Where η_s is transfer efficiency, E_S is the harvested energy of sensor node S and χ_s is the amount of energy transferred on the energy link 'e'. Let assume A and B are the departing data links and energy links respectively. The constraints of the energy serviceable can be rewritten by the following equation (5)

$$A_P + B_\chi \le E \tag{5}$$

3.1.3 Modified Negatively Correlated Search by Harris Hawks Optimization Algorithm
Modified Negatively Correlated Search by Harris Hawks Optimization algorithm is used for reducing Non convex problem in EH-WSN. Modified Negatively Correlated Search by Harris Hawks Optimization algorithm is a population-based search method. This algorithm has two phases. They are Exploration phase are used to find out the better candidate solution and exploitation phase are used to share the information between individuals to unequivocally give confidence for search process individually to region interest that are not explored by others. The penalty function approaches from Modified Negatively Correlated Search by Harris Hawks Optimization algorithm are used for finding the non-convex optimization problem. Let assume the optimization problem are given below in equation (6)

$$\min q_0(PA) \tag{6}$$

The equation (16) shows that

$$q_X(PA) \le 0, where\ X = 1,....,r., \tag{7}$$

Where q_0 is the objective function in network delay. Then the external penalty function for the optimization problem (6) can be written as

$$\phi(PA, m_1) = q_0(PA) + m_1 \sum_{X=1}^{r} [\max(0, q_X(PA)]^{qc}, \tag{8}$$

Where m_1 is a positive penalty parameter, 'qc' is a non-negative constant, and r is the number of constraint functions.

3.2 Step-by-Step Procedure for Non-Convex Problem in EHWSN

In this section, we are exploiting a promising constrained as Modified Negatively Correlated Search by Harris Hawks Optimization algorithm for attaining optimal energy transfer and minimum network delay. The detailed Step-by-step procedure and flow chart for Non-convex problem is explained as follows and given below in Figure 1.

Step 1: Initialization

Initialize the population size as S, power allocation vector as PA for getting possible solution, Number of active links in the network as AL.

Step 2: Random Generation

In random generation, each power allocation vector PA is randomly generated in S under the exploitable energy constraint consists of d transmission powers for first population by Setting

$$PA_X^Y, \quad X = 1,2,....,S; \quad Y = 1,2,........,d^* \tag{9}$$

Step 3: Estimation of Minimum Network Delay

For each initial power allocation vector PA, the minimum network delay $\phi(PA, m_1)$ can be computed [equation 8] using Modified Negatively Correlated Search Harries Hawks Optimization for recording preeminent Power Allocation vector of X^{th} node is given by

$$PA_X^* \leftarrow \arg\min_{PA_X} \times \phi(PA, m_1) \text{, where X=1, 2… S.} \tag{10}$$

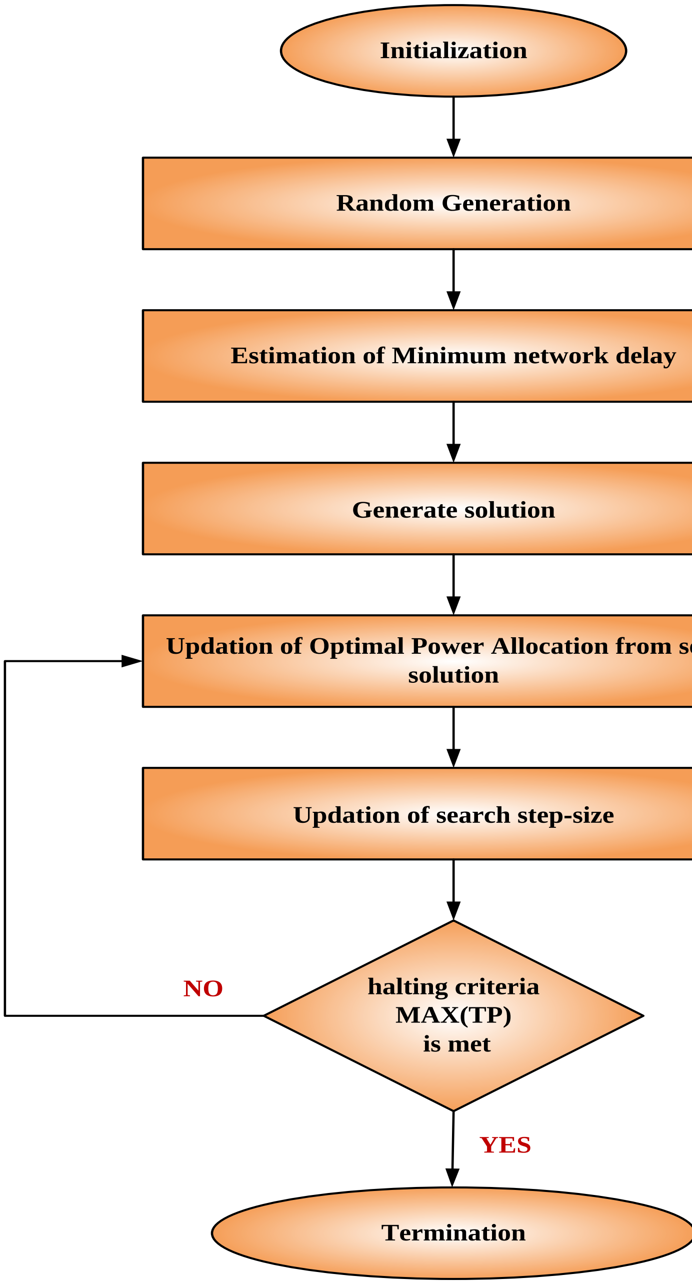

Figure 1: Flowchart for Non-convex problem optimization

Step 4: Generate solution

Before generating solution, the Bhattacharyya distance for two continuous and discrete probability distributions are given by

$$D_B(PA_X, PA_Y) = -\ln(\int \sqrt{PA_X(i) PA_Y(i) di}\,) \tag{11}$$

Where PA_X and PA_Y denote the probability, density functions of two distributions, 'i' denote the current solution obtained by the X[th] node. In each iteration of Modified Negatively Correlated Search Harries Hawks Optimization for Energy Delay Scheduling, the new power allocation vectors PA'_X are generated according to the Gaussian mutation operator σ_X to PA_X, similarly estimate the network delay $\phi(PA'_X, m_1)$ and Bhattacharyya distance for probability distribution $Corr(PA \times m_X)$, $Corr(PA' \times m_X)$ are given below in equation (12-13)

$$Corr(PA \times m_X) = \min_Y \left(D_B(PA_X, PA_Y) Y \neq X \right) \quad (12)$$

$$Corr(PA' \times m_X) = \min_Y \left(D_B(PA'_X, PA'_Y) Y \neq X \right) \quad (13)$$

Step 5: Updation of Optimal Power Allocation from Select Solution

For updating optimal power allocation, if the value of $\phi(PA'_X, m_1)$ is lesser than $\phi(PA^*_X, m_1)$ Then the optimal power allocation can be updated by replacing PA^*_X with PA'_X .The condition whether to replace power allocation vector PA_X with PA'_X is given by satisfying the following condition

$\frac{\phi(PA'_X, m_1)}{Corr(PA' \times m_X)} < \lambda_p$, then power allocation vector can be replaced as PA_X with PA'_X .

Where, $MAX(TP)$ is the user-defined total number of iterations for an execution of MNCS HHO

$$\lambda_p \leftarrow S(1, 0.1 - 0.1 * \frac{P}{MAX(TP)} \quad (14)$$

Since ϕ and $Corr$ may be of different scales, the two terms are normalized by requiring equal to $\phi(PA'_X, m_1) + \phi(PA^*_X, m_1)$ and $Corr(PA \times m_X) + Corr(PA' \times m_X)$ are equal to 1.

Step 6: Updation of search step-size

At each epoch iteration, updating the search step-size σ_X for each Randomized Local Search (RLS) using equation (15)

$$\sigma_X = \begin{cases} \frac{\sigma_X}{m} & if\ \frac{RT}{epoch} > 0.2 \\ \sigma_X * m & if\ \frac{RT}{epoch} < 0.2 \\ \sigma_X & if\ \frac{RT}{epoch} = 0.2 \end{cases}, \quad (15)$$

Where m is a parameter and RT is the replacement times during the past epoch iterations.

Step 7: Termination

Then Modified Negatively Correlated Search Harries Hawks Optimization for Energy Delay Scheduling will iteratively repeat the step 5 and 6 until the halting criteria $MAX(TP)$ is met. Finally, the outputs of Modified Negatively Correlated Search Harries Hawks Optimization for Energy Delay Scheduling are the optimal power allocation vector and the minimum network delay.

3.3 Computational Complexity of MNCSHHO

In MNCSHHO initialize solution, it has a computational complexity of network delay evaluation is O (S × AL*) by randomly generating each power allocation vector PA_X in population. At each iteration of MNCSHHO, the computational complexity of generating new solution is O (S × AL*) according to the Gaussian mutation operator. Therefore, the computation complexity of MNCSHHO is O (MAX (TP) ×S × AL*). For a given MAX (TP), the computation complexity of MNCSHHO depends on the number of active links AL and the population size S.

4. Result and Discussion

In this section, simulation evaluations of the proposed EDS-MNCSHHO and MNCSHHO algorithms are discussed for the Non-convex problem. Here network performance of EH-WSNs with interference channel is also discussed. The simulations are conducted on a PC with the Intel Core i5, 2.50 GHz CPU, 8GB RAM and Windows 7. All simulation programs are implemented within Network simulator (NS2). The network characteristics parameters are given below in table 1.

4.1 Simulation Phase 1: Performance Comparison of Various Algorithm

Figure 2 -7 shows the Simulation result for capacity assignment problem in EH-WSN for fixed data flows. To better evaluate the network performance of proposed Modified Negatively Correlated Search by Harris Hawks Optimization algorithm (EDS-MNCSHHO) this was compared with the existing algorithm such as EDS-NCS, convex approximation [29] respectively.

Table 1: Network Parameter for Simulation

Parameter	Value
Noise power on data link	1×10^{-5} units
Transfer efficiency	0.6
SINR threshold value	5
Population size	50
Total number of time periods in a data collection round.	300
Penalty parameter m_1	1×10^{30}
Epoch	10
Number of nodes	100

From figure 2 shows the node delay performance, at node 20, the proposed EDS-MNCSHHO shows node delay 15%, 43% lower than existing EDS-NCS, convex approximation respectively. At node 40, the proposed EDS-MNCSHHO shows node delay 28%, 52% lower than existing EDS-NCS, convex approximation respectively. At node 60, the proposed EDS-MNCSHHO shows node delay 20%, 38.5 % lower than existing EDS-NCS, convex approximation respectively. At node 80, the proposed EDS-MNCSHHO shows node delay 17%, 34.9% lower than existing EDS-NCS, convex approximation respectively. At node 100, the proposed EDS-MNCSHHO shows node delay 21.48%, 43.68% lower than existing EDS-NCS, convex approximation respectively.

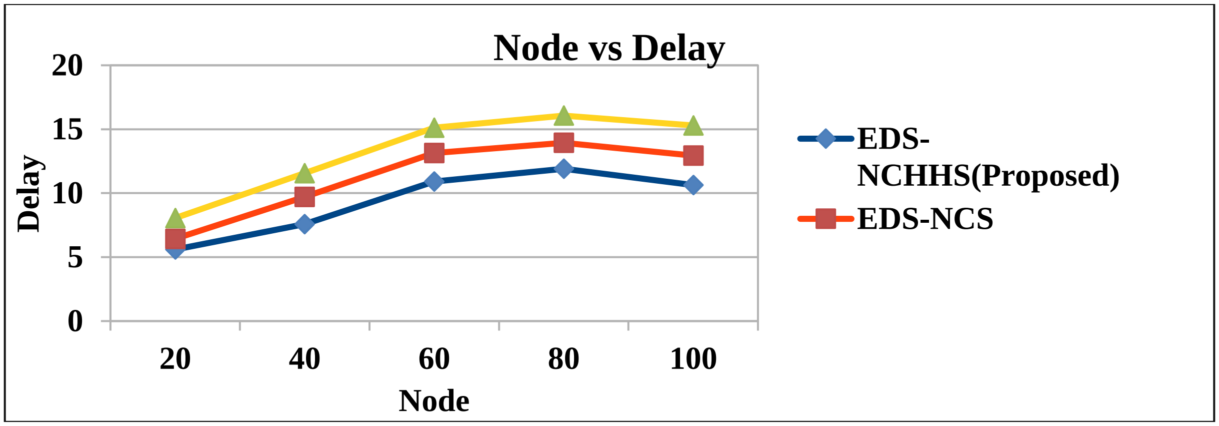

Figure 2: Performance Analysis of Node Delay

From figure 3 shows the packet drop performance, at node 20, the proposed EDS-MNCSHHO shows drop 3%, 1% lower than existing EDS-NCS, convex approximation respectively. At node 40, the proposed EDS-MNCSHHO shows packet drop 2.095%, 0.4285% lower than existing EDS-NCS, convex approximation respectively. At node 60, the proposed EDS-MNCSHHO shows packet drop 0.717%, 0.349% lower than existing EDS-NCS, convex approximation respectively. At node 80, the proposed EDS-MNCSHHO shows packet drop 4.365%, 0.707 % lower than existing EDS-NCS, convex approximation respectively. At node 100, the proposed EDS-MNCSHHO shows packet drop 1.554%, 0.861% lower than existing EDS-NCS, convex approximation respectively.

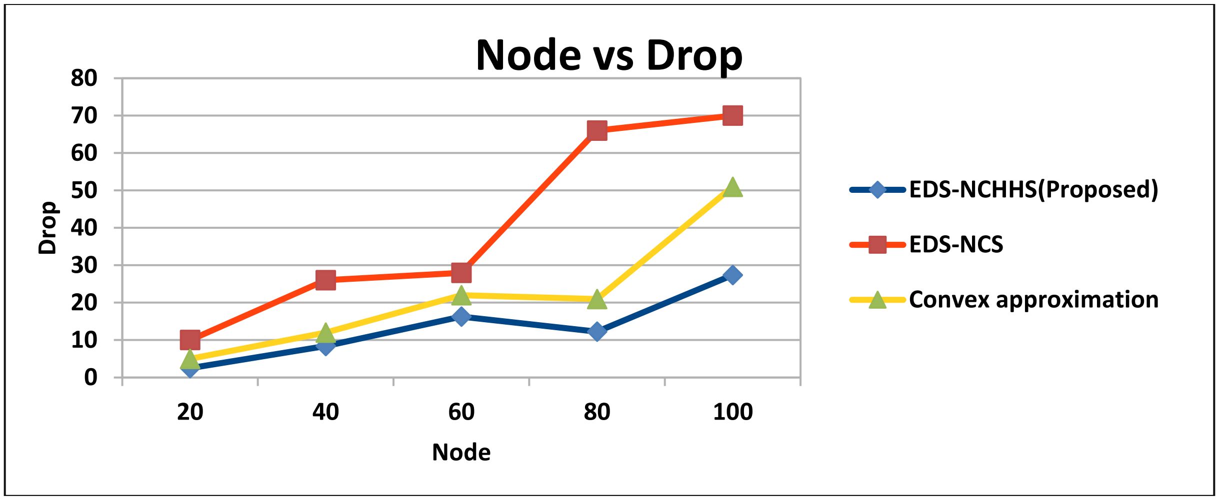

Figure 3: Performance Analysis of Drop

From figure 4 shows the node energy transfer performance, at node 20, the proposed EDS-MNCSHHO shows node energy transfer 21%, 60% lower than existing EDS-NCS, convex approximation respectively. At node 40, the proposed EDS-MNCSHHO shows node energy transfer 24.078%, 62.69% lower than existing EDS-NCS, convex approximation respectively. At node 60, the proposed EDS-MNCSHHO shows node energy transfer 25.84%, 0.349% lowers than existing EDS-NCS, convex approximation respectively. At node 80, the proposed EDS-MNCSHHO shows node energy transfer 25.84%, 66% lower than existing EDS-NCS, convex approximation respectively. At node 100, the proposed EDS-MNCSHHO shows node energy transfer 27.21%, 67.375 % lower than existing EDS-NCS, convex approximation respectively.

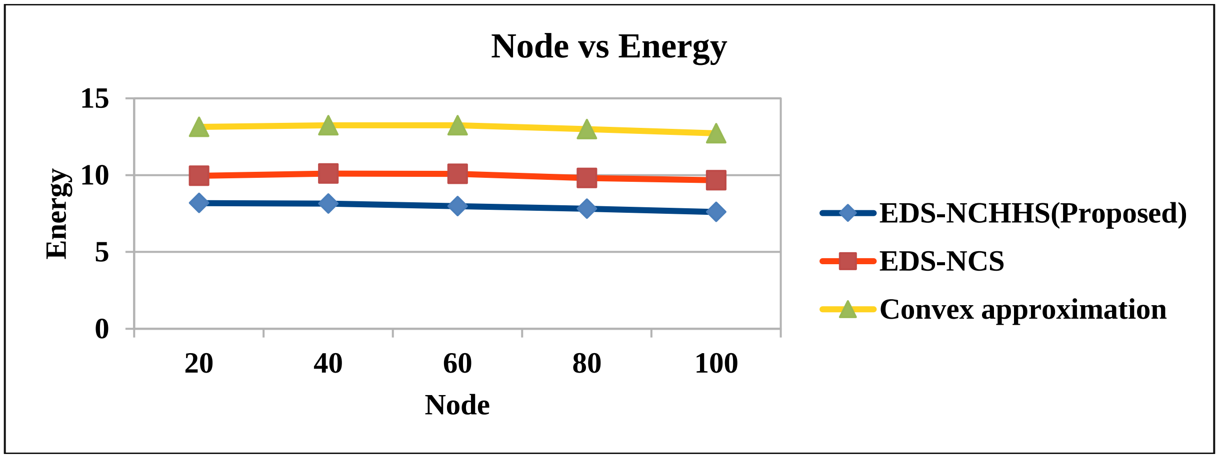

Figure 4: Performance Analysis of Energy Transfer

From figure 5 shows the network life time performance, at node 20, the proposed EDS-MNCSHHO shows network life time 0.927%, 2.018% higher than EDS-NCS, convex approximation respectively. At node 40, the proposed EDS-MNCSHHO shows network life time 0.913%, 2.0344% higher than EDS-NCS, convex approximation respectively. At node 60, the proposed EDS-MNCSHHO shows network life time 1.3%, 2.631% higher than EDS-NCS, convex approximation respectively. At node 80, the proposed EDS-MNCSHHO shows network life time 1.128%, 2.556% higher than EDS-NCS, convex approximation respectively. At node 100, the proposed EDS-MNCSHHO shows network life time 1.185%, 2.4705 % higher than EDS-NCS, convex approximation respectively.

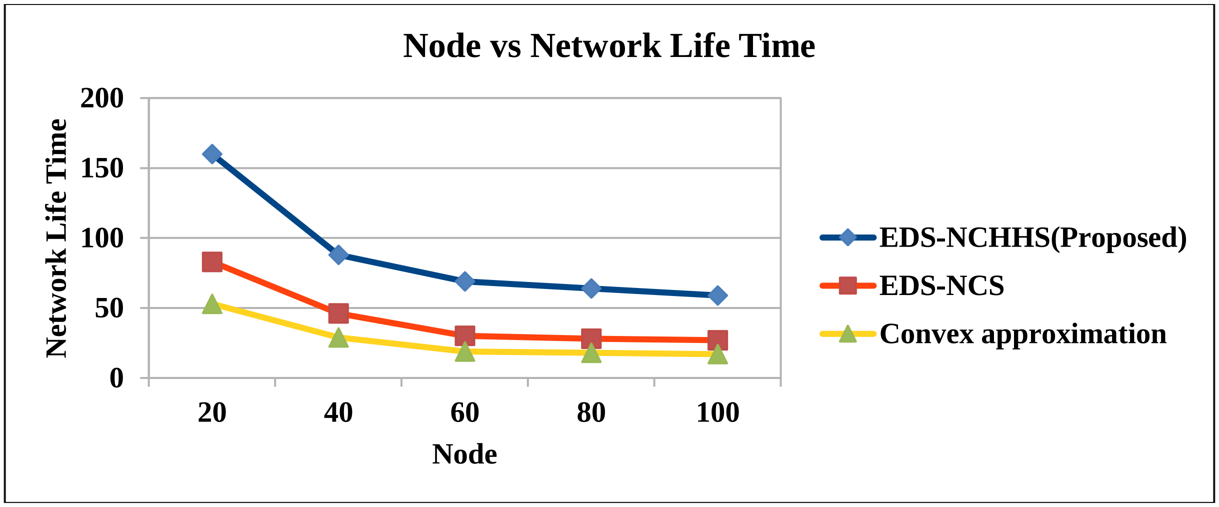

Figure 5: Performance Analysis of Network Life Time

From figure 6 shows the node overhead, at node 20, the proposed EDS-MNCSHHO shows node overhead 40%, 13.65% lower than existing EDS-NCS, convex approximation respectively. At node 40, the proposed EDS-MNCSHHO shows node overhead 51.85%, 27.627% lower than existing EDS-NCS, convex approximation respectively. At node 60, the proposed EDS-MNCSHHO shows node overhead 51.38%, 33.14% lower than existing EDS-NCS, convex approximation respectively. At node 80, the proposed EDS-MNCSHHO shows node overhead 1.128%, 2.556% lower than existing EDS-NCS, convex approximation respectively. At node 100, the proposed EDS-MNCSHHO shows node overhead 58.26%, 40.0338 % lower than existing EDS-NCS, convex approximation respectively.

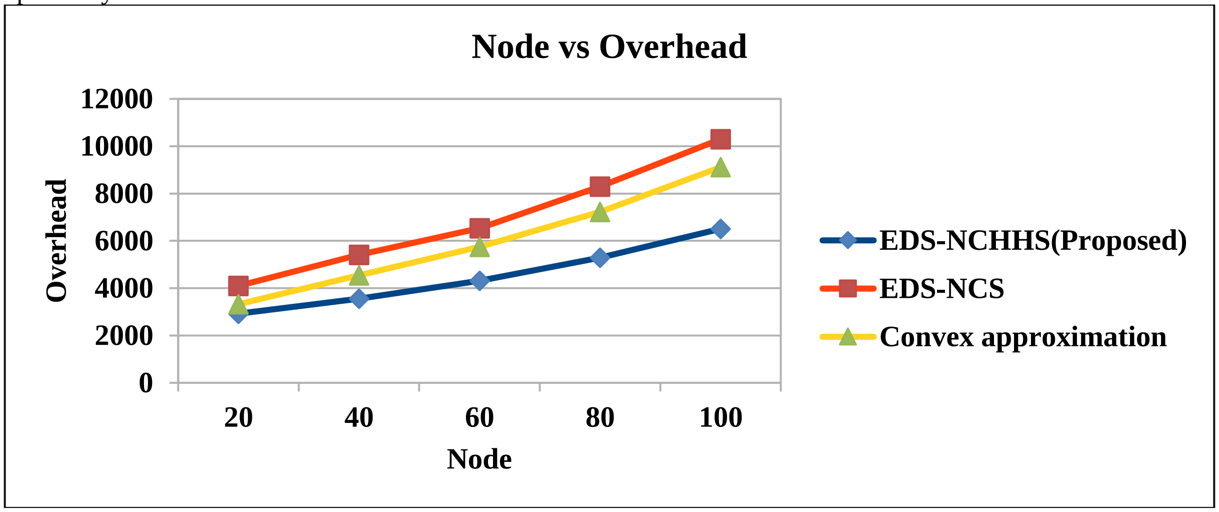

Figure 6: Performance Analysis of Overhead

From figure 7 shows the throughput, at node 20, the proposed EDS-MNCSHHO shows throughput 0.517%, 1.0219 % higher than EDS-NCS, convex approximation respectively. At node 40, the proposed EDS-MNCSHHO shows throughput 0.529%, 1.038% higher than EDS-NCS, convex approximation respectively. At node 60, the proposed EDS-MNCSHHO shows throughput 0.527%, 1.0326% higher than EDS-NCS, convex approximation respectively. At node 80, the proposed EDS-MNCSHHO shows throughput 0.523%, 1.0283% higher than EDS-NCS, convex approximation respectively. At node 100, the proposed EDS-MNCSHHO shows throughput 1.185%, 1.0023% higher than EDS-NCS, convex approximation respectively.

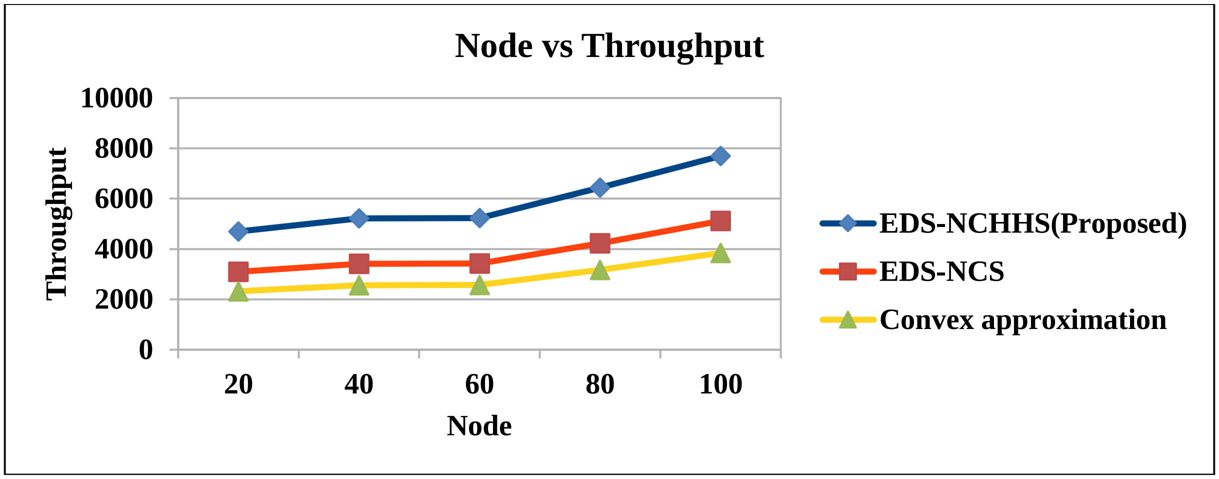

Figure 7: Performance Analysis of Throughput

4.2 Simulation Phase 2: Performance Analysis of various NCS Algorithm

Figure 8 -13 shows the Simulation result for various NCS algorithm. To better evaluate the network performance of proposed Energy delay scheduling Modified Negatively Correlated Search by Harris Hawks Optimization algorithm (MNCSHHO) this was compared with the existing algorithm such as NCS. From figure 8 shows the node delay in EH-WSN, at node 20, the proposed MNCSHHO algorithm shows node delay 49.913% lower than NCS algorithm. At node 40, the proposed MNCSHHO algorithm shows node delay 32.312% lower than existing NCS algorithm. At node 60, the proposed MNCSHHO algorithm shows node delay 23.7011% lower than existing NCS algorithm. At node 80, the proposed MNCSHHO algorithm shows node delay 15% lower than existing NCS algorithm. At node 100, the proposed MNCSHHO algorithm shows node delay 21% lower than existing NCS algorithm.

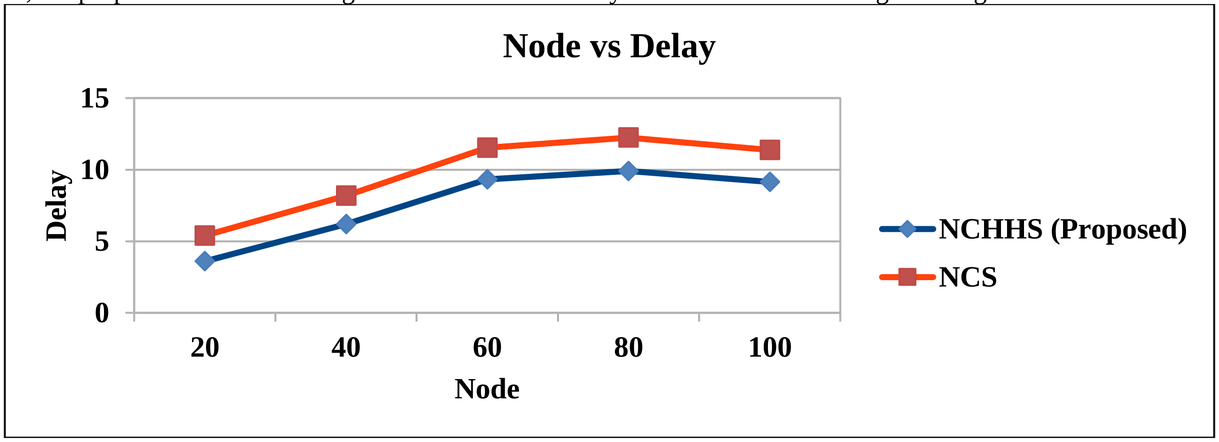

Figure 8: Performance Analysis of Delay

From figure 9 shows the drop performance in EH-WSN, at node 20, the proposed MNCSHHO algorithm shows packet drop 1.543% lower than existing NCS algorithm. At node 40, the proposed MNCSHHO algorithm shows packet drop 0.1875% lower than existing NCS algorithm. At node 60, the proposed MNCSHHO algorithm shows packet drop 0.692% lower than existing NCS algorithm. At node 80, the proposed MNCSHHO algorithm shows packet drop 1.0833% lower than existing NCS algorithm. At node 100, the proposed MNCSHHO algorithm shows packet drop 0.28% lower than existing NCS algorithm.

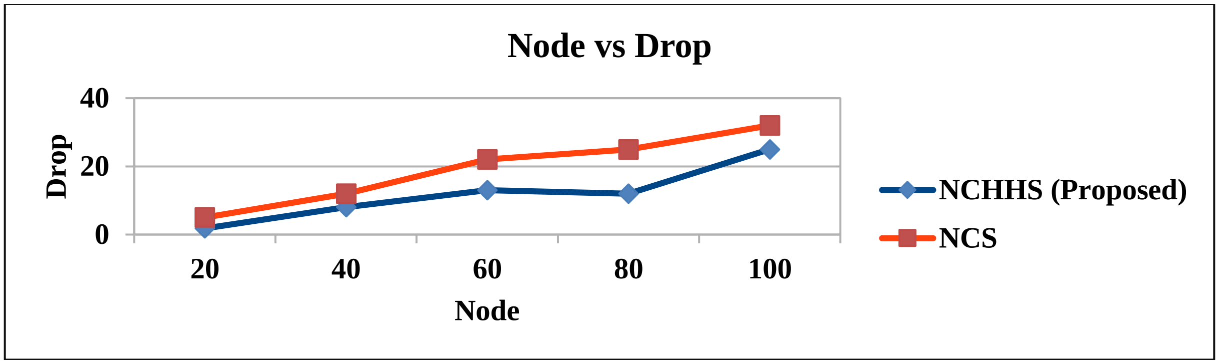

Figure 9: Performance Analysis of Drop in EH-WSN

From figure 10 shows the node energy transfer in EH-WSN, at node 20, the proposed MNCSHHO algorithm shows energy transfer 2.64% lower than NCS algorithm. At node 40, the proposed MNCSHHO algorithm shows energy transfer 1.658% lower than NCS algorithm. At node 60, the proposed MNCSHHO algorithm shows energy transfer 3.95% lower than NCS algorithm. At node 80, the proposed MNCSHHO algorithm shows energy transfer 8.309% lower than NCS algorithm. At node 100, the proposed MNCSHHO algorithm shows energy transfer 3.424% lower than NCS algorithm.

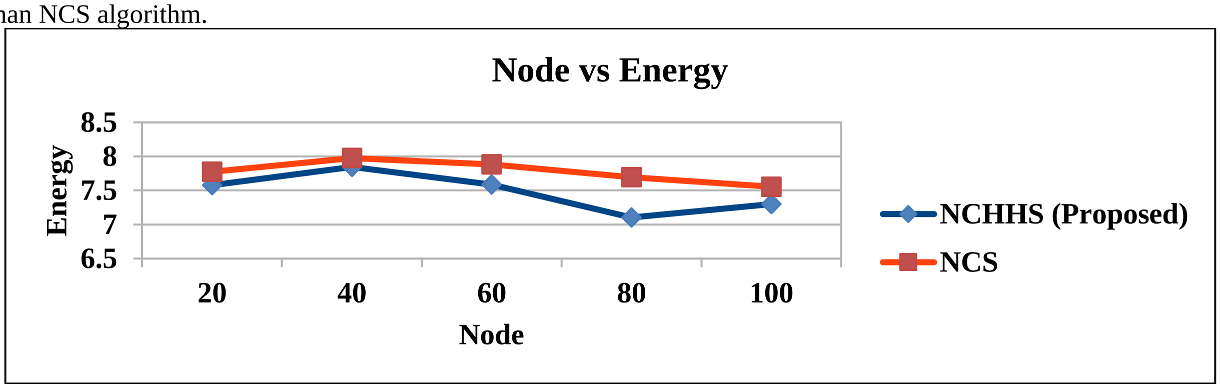

Figure 10: Performance of Energy Transfer in EH-WSN

From figure 11 shows the network time delay in EH-WSN, at node 20, the proposed MNCSHHO algorithm shows network time delay 37.93% higher than NCS algorithm. At node 40, the proposed MNCSHHO algorithm shows network time delay 28.947% higher than NCS algorithm. At node 60, the proposed MNCSHHO algorithm shows network time delay 64.28% higher than NCS algorithm. At node 80, the proposed MNCSHHO algorithm shows network time delay 64.10% higher than NCS algorithm. At node 100, the proposed MNCSHHO algorithm shows network time delay 63.157% higher than NCS algorithm.

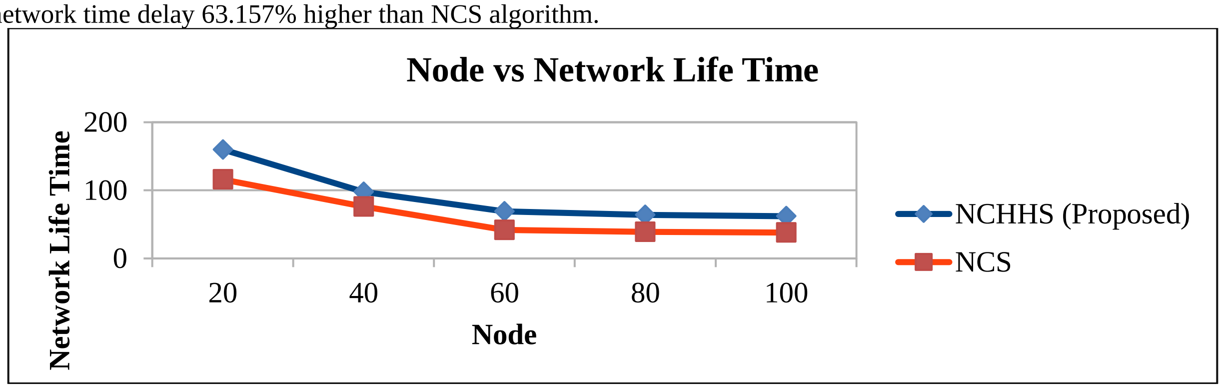

Figure 11: Network Life Time in EH-WSN

From figure 12 shows the overhead graph in EH-WSN, at node 20, the proposed MNCSHHO algorithm shows overhead 0.7918% lower than NCS algorithm. At node 40, the proposed MNCSHHO algorithm shows overhead 0.9946% lower than NCS algorithm. At node 60, the proposed MNCSHHO algorithm shows overhead 0.7527% lower than NCS algorithm. At node 80, the proposed MNCSHHO algorithm shows overhead 0.729% lower than NCS algorithm. At node 100, the proposed MNCSHHO algorithm shows overhead 0.7776% lower than NCS algorithm.

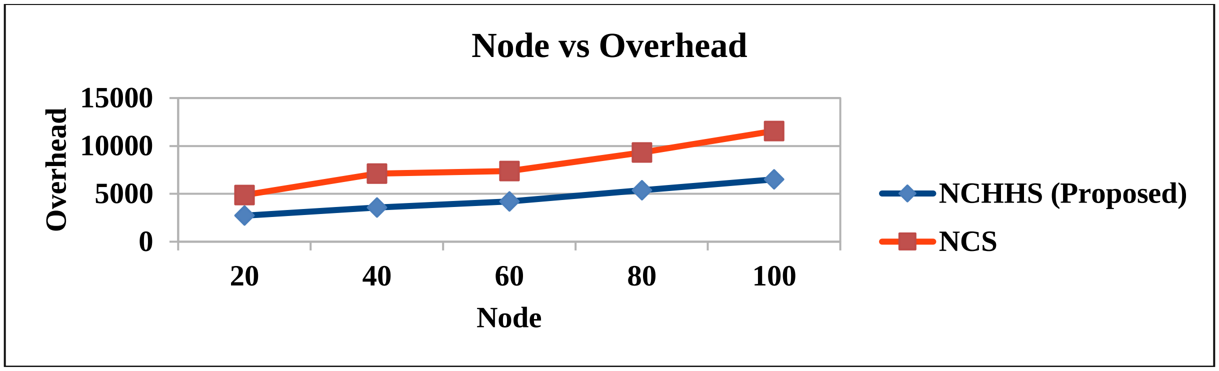

Figure 12: Overhead in EH-WSN

From figure 13 shows the throughput graph in EH-WSN, at node 20, the proposed MNCSHHO algorithm shows throughput 17.16% higher than NCS algorithm. At node 40, the proposed MNCSHHO algorithm shows throughput 26.226% higher than NCS algorithm. At node 60, the proposed MNCSHHO algorithm shows throughput 22.09% higher than NCS algorithm. At node 80, the proposed MNCSHHO algorithm shows throughput 21.83% higher than NCS algorithm. At node 100, the proposed MNCSHHO algorithm shows throughput 21.5033% higher than NCS algorithm.

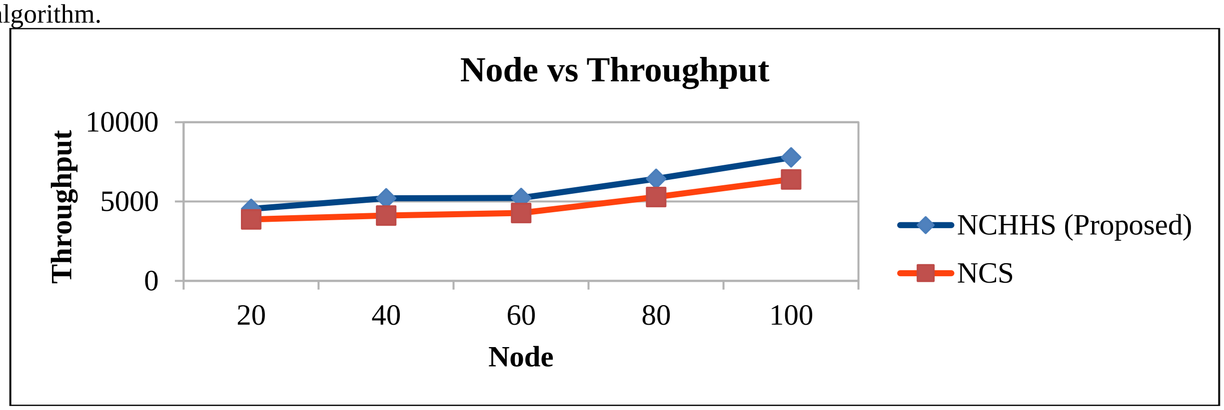

Figure 13: Performance Analysis of Throughput in EH-WSN

5. Conclusion

This manuscript presents a Modified Negatively Correlated Search by Harris Hawks Optimization (MNCSHHO) algorithm for EH-WSNs with interference channel to solve the Non convex problems. The proposed algorithm optimizes data rates and energy transfers. By this total network delay can be minimized. The simulations are performed using Network Simulator (NS2) to validate the performance of the proposed Modified Negatively Correlated Search by Harris Hawks Optimization (MNCSHHO) algorithm and it provide better results compared with the existing algorithms like EDS-NCS, convex approximation respectively. The solution of this paper could also be beneficial to other complex optimization problems in the energy harvesting wireless network design.

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