Shuffled Shepherd Squirrel Optimization and Fractional LMS Model for In-Network Aggregation in Wireless Sensor Network

Rajesh L., SJB Institute of Technology, VTU University, India*
Mohan H. S., New Horizon College of Engineering, VTU University, India

ABSTRACT

The wireless sensor network (WSN) is commonly based on small node collaboration. These nodes are specified by wireless communication, low price, and energy consumption. Moreover, the WSN can be utilized to compute pressure, temperature, as well as monitoring health, military supervision, and so on. A variety of WSN applications need to gather data from sensor nodes based on sink. In this paper, shuffled shepherd squirrel optimization (SSSOA) technique is devised for in-network aggregation in WSN. Here, the path is formulated from source node to destination through routing process, and source node broadcasts a packet concurrently to destination. The WSN is initiated, and the suitable cluster head (CH) is selected from all nodes. Consequently, CH is selected based on the developed shuffled shepherd squirrel optimization (SSSOA) method.

KEYWORDS

Cluster Head, Route Maintenance, Routing, Sink Node, Wireless Sensor Network

1. INTRODUCTION

Normally, WSN is based on assistance of small nodes. These small nodes are mainly precised with low cost, less energy utilization and wireless communications. The WSN is utilized to measure health monitoring, surveillance (Alfonso Marino, 2019), pressure, and temperature, military and so on (Bharat Bhushan and Gadadhar Sahoo, 2020). However, it has various limitations in energy, power (Gayathri Devi K.S, 2019), security and memory. The energy and trust are most important factors for assessment process because of natural limitations of computing power and source of sensor nodes. The assurance of security in WSN directs to more energy saving and various beneficial problems (Zahedi and Parma, 2019). In addition, WSN collects various information of locality by constant monitoring and it is employed in Body Area Network (BAN), because it is inexpensive and establishment process is simple (Negra, *et al*., 2016; Mahesh and Vijayachitra, 2019). Besides BAN, WSN is applied for military tracking, fire monitoring etc (Bharat Bhushan, and Gadadhar Sahoo, 2018). WSN acquires short range sensors, which is engaged in environment monitoring (John and Rodrigues, 2019). The sensor nodesare normally included with several parameters, such as storage capacity, energy constraints and insufficient computation. In WSN, every routing protocols change with application through alternate goals (Negra, *et al*., 2016; Mahesh and Vijayachitra, 2019). Normally, WSN performs with sensor nodes, which works on battery and hence, energy is a main limitation of WSN (Satish Chand,

DOI: 10.4018/IJBDCN.309412
*Corresponding Author

Samayveer Singh and Bijendra Kumar, 2014). The battery operated sensors is more dependable for the lifetime of network (Hammoudeh and Newman, 2013; Mahesh and Vijayachitra, 2019). Moreover, clustering is a process, which controls energy expenditure of sensor nodes through creating groups, termed as clusters. The clusters are generated along with cluster controller (Neenavath Veeraiah and Dr.B.T.Krishna, 2018), CH, while another node is Cluster Members (CMs). The sensor node belongs to particular cluster and it employed them selves for transferring gathered data to CH (Bharat Bhushan, and Gadadhar Sahoo, 2017). Furthermore, CH is communicated to Base Station (BS) by multi hop or single hop communication (Lee and Cheng, 2012; Mahesh and Vijayachitra, 2019).

The CH Selection (CHS) process guarantees that nodes in a network have similar possibility to become as CH. The purpose of CH is to classify node data and transmits it to BS (Kang and Nguyen, 2012; John and Rodrigues, 2019). The CHs are selected (Amit Kelotra and Prateek Pandey,2019) for maintaining energy load balance and power energy utilization in each set of sensor node (Bharat Bhushan, and Gadadhar Sahoo, 2019). Apart from this, bottleneck issues in a linked dominating set was avoided through generating virtual dominator with Steiner tree construction. Additionally, computational complication was decreased for maintaining remaining energy of sensor nodes, hence WSN life span is enlarged. The routing protocols were designed based on various applications (Gautam and Pyun, 2010; John and Rodrigues, 2019). The cluster-based routing protocols (C. Srinivas M. Naga Jaya Sree, and P. Vijay Kumar, 2019) are utilized for improving network duration by attaining ideal load balance and minimization of communication volume (John and Rodrigues, 2019). Routing in sensor network (Rajesh, Ganesan, Raajini, Xavier Mercilin, Sagayam, Kulandairaj Martin, Bhushan, Bharat, Kose, and Utku, 2020) is a recent research area and liability of routing protocol is for enabling sensor nodes (Dr. S. R. Mugunthan, 2021) to choose routes between sink node and source node (Ge, *et al*., 2018; Sama, *et al*., 2019). The processing ability offered by traditional sensor node is utilized for optimizing routing task. The aforementioned process is named as data centric routing or in-network data aggregation. The sensor nodes must be configured through local decision making for effective and efficient data gathering process with less utilization of restricted resources (Chatzigiannakis, *et al*., 2006; Villas, *et al*., 2012).

Data aggregation is employed for combining every data packets. Data aggregation is also possible to remove meaningless or redundant data also it decreases volume and quantity of transmissions. Therefore, data aggregation approach was effectively decreased energy consumption in WSN (Vinusha and Abinaya, 2018). Moreover, data packets are combined together by aggregation function, like sum, variance, median, average, standard deviation, count and so on. The combined data packets are utilized for reducing energy consumption, network delay, communication cost network congestion and bandwidth utilization in WSN routing (Ardakani, 2017). Moreover, data aggregation is the efficient approach for energy saving in WSNs. The natural redundancy present in data is gathered through sensor node to overcome this redundancy problem. The network lifetime is enlarged, while minimum communication directs to energy saving (Villas, *et al*., 2012). In WSN, the data aggregation allows in-network processing, and it directs to minimum redundancy and less data packet transmission rate. Various research works are developed by Elliptic Curve ElGamal homomorphic encryption technique for protecting data confidentiality (Uvarajan and Shankar, 2020). The overall network overhead and energy expenditure associated with the multi hop data retrieval process however the process of data aggregation and fusion among clusters needs to be explored ((A. Manickavasuki and R. Ramya, 2014). The use of pallier crypto system which is resilient to false data injection attacks. It improving network duration and shows more computational complication ((Vishal Krishna Singh and Saurabh Verma Manish Kumar, 2016).

WSN has many benefits like they can be implemented almost anywhere without the need for any specific communication infrastructure. However they have limitations in power, energy consumption and security. Thus it is necessary to design an efficient in-network aggregation method. Different existing methods are in practice, however they limit due to many reason like failure of nodes, complex route identification, flexibility, node failure probability, energy hole issues, etc., which motivates the author to develop a new method. The primary goal of this research is to devise and develop an approach for In-Network Aggregation in WSN. The path is created from source node to destinations through routing protocols. The source node sends a packet to destination concurrently. Initially, WSN is initialized and CHS is processed from nodes. The CH is selected based on SSSOA. The SSSOA is developed by integrating SSOA (Kaveh and Zaerreza, 2020) and SSA (Jain, *et al.*, 2019). The path with lowest distance is chosen as optimal path by means of multi-objective functions, like distance, energy, link quality, and delay. Subsequently, route maintenance method is performed in simulated network using link quality metric in case of link failures. Once the route maintenance is performed, data aggregation and data reduction is carried out based on HFBLMS (Ganjewar, *et al.*, 2018).

The major contribution of this research is represented as below:

- **Developed SSSOA for In-Network Aggregation in WSN:** The SSSOA is developed for In-network aggregation in WSN, SSSOA is the combination of SSOA and SSA. Here, the optimal CH is selected using various multi objective functions, namely delay, energy, distance and link quality.

The rest of the paper is arranged as following way: Section 2 explains about inspiration and literature review on data aggregation and routing schemes in WSN, section 3 illustrates the developed SSSOA for In-network aggregation. Section 4 signifies the results and discussions obtained by developed SSSOA, and at last section 5 terminates the chapter.

2. MOTIVATION

This section illustrates about numerous challenges faced by existing In-Network Aggregation methods in WSN. These challenges are considered for producing a novel approach for In-Network Aggregation methods in WSN using SSSOA.

2.1 Literature Survey

This section illustrates literature survey of various approaches devised for In-Network Aggregation in WSN, and the challenges of present works are explained. Leandro Villas *et al.* (Villas, *et al.*, 2012) developed Data Routing for In-Network Aggregation (DRINA) scheme for routing in WSN. This method includes various key features, like reliable data transmission and aggregation, high aggregation rate, maximum amount of overlapping routes and reduced amount of messages for developing routing tree. The developed approach involves various roles, like sink, collaborator, relay and coordinator in routing formation. This developed method was separated into three basic levels. The hop tree was generated from sensor node to sink node in level-1, and developed hop tree was utilized by coordinators for forwarding data. CHS and cluster formation between nodes was considered in level-2, which easily identifies the presence of new events in a network. At last, new route was formulated in level-3 for consistent delivery of packets and hop tree. This method effectively reduced overlapping routes and achieved high aggregation rate. However, this method not included temporal and spatial correlation of aggregated data to produce routing tree. Ganjewar P D *et al.* (Ganjewar, *et al.*, 2018) modelled Hierarchical Fractional Bidirectional Least-Mean Square (HFBLMS) technique for reducing data in WSN. This scheme was developed through changing Hierarchical Least Mean Square (HLMS) method with Fractional Calculus (FC) and Bidirectional Least Mean Square (BLMS) in weight update procedure. Finally, developed HFBLMS approach was effectively decreased the network energy consumption. Here, energy needed for transmitting data through sensor node was decreased withimproved network lifetime. However, experimentation of this method was not executed by placing skin node at everywhere for better performance. Nisha and Basha, (2020) introduced Triangular Fuzzy-based Spectral Cluster Routing (TF-SCR) model for energy-efficient routing in WSN. Initially, pre-processing was employed in which received signal strength and residual energy of every sensor node was identified. After that, clustering process was executed, where every sensor nodes were grouped using residual energy level. Moreover, triangular fuzzy membership function was utilized to choose CH for routing process of data packets to base station. This scheme highly increases the reliability and network lifetime of data packet transmission in WSN even though, dependability of data packet transmission was still inexplicable.

Zhang, *et al*., (2020) developed Entropy-driven Data Aggregation with Gradient Distribution (EDAGD) exploitation method for energy efficiency in WSN. This technique was mainly developed based on three approaches, namely Entropy driven aggregation Tree-based routing Approach, Multihop Tree-based Data Aggregation (MTDA) process and Gradient Deployment Algorithm (GDA). Here, MTDA approach was applied for decreasing data transmission distance during communication process. Along with this ETA was also employed using Choquet entropy and integral and it was used for monitoring the irregular events. Finally, GDA was also executed for controlling energy hole issues. This approach effectively enhances the lifetime of WSN even though, this scheme was difficult process with high level performances. Bongale, *et al*., (2020) modelled Intra Cluster data Aggregation approach (ICA) for WSN. This method creates ICA path from source node to CH node. This approach mainly includes three stages, such as cluster formation level, ICA path formation and data transmission stage. This scheme achieved decreased amount of data message transmission and enhanced the energy efficiency. Although, this process not computed the performance of ICA through increasing the amount of nodes. Haseeb, *et al*., (2020) introduced Light-weight structure-based Data Aggregation Routing (LSDAR) method for enhancing energy routing performance. At first, network nodes were decomposed into single cluster using different radiuses of base station. After that, effective and loop free routing paths were formulated using A-star heuristics approach. Consequently, communication links were confined based on One Time Pad (OTP) method, which was utilized for data security. This method has less memory consumption and high data protection but, the channel condition and network status were not analyzed for selecting next hop. Uvarajan and Shankar, (2020) introduced Trust Assisted Global and Greedy Congestion-aware Data Aggregation (TAG–GCDA) for WSN. This scheme was named as threefold homogenous technique, which was developed for monitoring energy efficient routing and data aggregation, secure neighbour selection with greedy technique. This technique improves global aggregation precision with limited conditions in aggregation. This technique was also ensures trusted neighbour selection using greedy congestion control and energy conservation. In addition, this scheme decreases energy consumption and communication overhead with various route requests. However, this approach not addressed the presence of attacks at several layers. Ardakani, (2017) introduced data aggregation routing protocols in WSN. This data aggregation process consists of two methods, namely client/server and mobile agent. The server or client scheme was applied to accumulate and combined the data packets from event to sink. Furthermore, mobile agents were utilized for transfer the data samples at source node. This routing process was achieves high routing scalability, stability and extendibility but still, it consumes high energy and the network lifetime was less.

2.2 Challenges

The difficulties faced by presentIn-Network Aggregation methods in WSN are discussed below.

- The DRINA (Villas, *et al*., 2012) approach was developed for in-network aggregation in WSN, but still this method was not developed new techniques to manage waiting time for aggregator nodes using two measures, namely spatial and semantics event correlation and average distance of event coordinators.
- The TF-SCR technique was introduced for energy efficient routing in a WSN (Nisha and Basha, 2020). Although, this method was not developed as secure routing for improving packet delivery ratio and reducing data loss because of cruel attacks in a WSN.
- The LSDAR method (Haseeb, *et al*., 2020) was combined with next generation sensor network for energy efficient routing. However, this method was not flexible in failure of nodes and route identification was also complex one.

- The data aggregation routing method was developed in (Ardakani, 2017) for reducing transmission amount and joining data packets even though, distributed methods was not included for solving bottleneck issues and reducing partial node failure probability.
- The EDAGD approach (Zhang, *et al.*, 2020) was developed for energy efficient WSN however, this method failed to introduce non-uniform sensor distribution approach for solving energy hole issues.

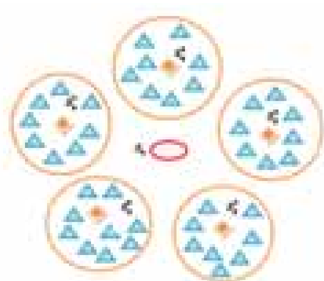
3. SYSTEM MODEL

The network model, energy model and link life model is considered in this system model and it is explained as follows.

3.1 NETWORK MODEL

The WSN includes one sink node S_n with m sensor nodes. The wireless links denotes the direct communication among sensor nodes in a radio range. Each sensor nodes are equivalently allocated in sizes of M_l and N_l in meters having its highest communication radio range. In addition, every sensor node has individual distinctive identification and it assembled in clusters. Base station is placed in the position of $\left\{0.5M_l, 0.5N_l\right\}$ and it is predetermined near optimal solution for receiving data symbols from nodes, which are linked to this network. The position of sensor nodes is estimated by its coordinate values of M_p and N_p. The data transfer to sink node from each sensor node is performed by means of cluster head-based routing method. In this model, A_o is amount of sensor nodes stimulated as cluster head $\left(S_q\right)$. A_o^y is group of sensor nodes in a cluster group, A_o. The sensor network is separated into A_o amount of cluster in which total number of normal nodes is equivalent to $y - A_o$. After the generation of cluster groups in sensor network, data packets are transmitted from each node K to equivalent CH S_q and CH gathered every data packets. Then, gathered data packets are transmitted to BS S_n. Once the total sensor node is installed to predetermined position then, the distance among p^{th} normal node to Z^{th} CH is represented as, $r_{p,Z}$ and distance among Z^{th} cluster head to base station S_n is illustrated as x_Z (Kumar and Kumar, 2016). The system representation of WSN is displayed in figure 1.

Figure 1. System model of WSN



3.2 Energy Model

Each sensor node has an initial energy, I_0 and statement is that, sensor node energy cannot be re-energized. Each packet transfers energy loss from p^{th} normal node Z^{th} cluster head follows a multi path fading method (Heinzelman, *et al.*, 2002; Kumar and Kumar, 2016) and free space and it is based on distance between receiver and transmitter. The data transfer follows Time Division Multiple Access (TDMA) protocol and also each node has hardware of receiver and transmitter. The transmitter has power amplifier and radio electronics for dissipating energy. Similarly, receiver has radio electronics for dissipating energy. In addition, energy dissipation for each packet of dimension B_s follows two various energy dissipation methods and it is based on nature and distance of node (Kumar and Kumar, 2016). If normal node transmits B_s bytes of data, at that momentthe energy dissipation of normal node is expressed as below.

$$E_d\left(K^b\right) = E_e * B_s + E_a * B_s * \left\|K^b - S_q^b\right\|^4 \text{ if } \left\|K^b - S_q^b\right\| \geq C_0 \tag{1}$$

$$E_d\left(K^b\right) = E_e * B_s + E_{kw} * B_s * \left\|K^b - S_q^b\right\|^2 \text{ if } \left\|K^b - S_q^b\right\| < C_0 \tag{2}$$

$$R_{c0} = \sqrt{\frac{E_{kw}}{E_{at}}} \tag{3}$$

where, E_e represents electronic energy using various aspects, such asamplifier, modulation, filtering, spreading and digital coding.

$$E_e = E_T + E_D \tag{4}$$

where, E_T denotes transmitted energy and E_D illustrates data aggregation. Likewise, E_{at} is energy parameter correlated to power amplifier in a transmitter. $\left\|K^b - S_q^b\right\|$ is distance among cluster head and normal node.

If the CH node obtains B_s bytes of data then, energy dissipation through receiver is signified as below,

$$E_d\left(S_q^b\right) = E_e * B_s \tag{5}$$

Energy value of each node is updated over again after receiving or sending B_s bytes of data.

$$E_{f+1}\left(K^b\right) = E_f\left(K^b\right) - E_d\left(K^b\right) \tag{6}$$

$$E_{f+1}\left(S_q^b\right) = E_f\left(S_q^b\right) - E_d\left(S_q^b\right) \tag{7}$$

This data transfer procedure is repetitive until each node is, named as dead node. The energy of a node is smaller than zero then, it is said as dead node.

3.3 Link Life Time Model

Link Life Time(LLT; Balachandra, *et al*., 2014) is computed at every hop in path traversal of a route request packet. Every node estimates LLT among previous hop and current hop. The link life time is calculated by using below equation,

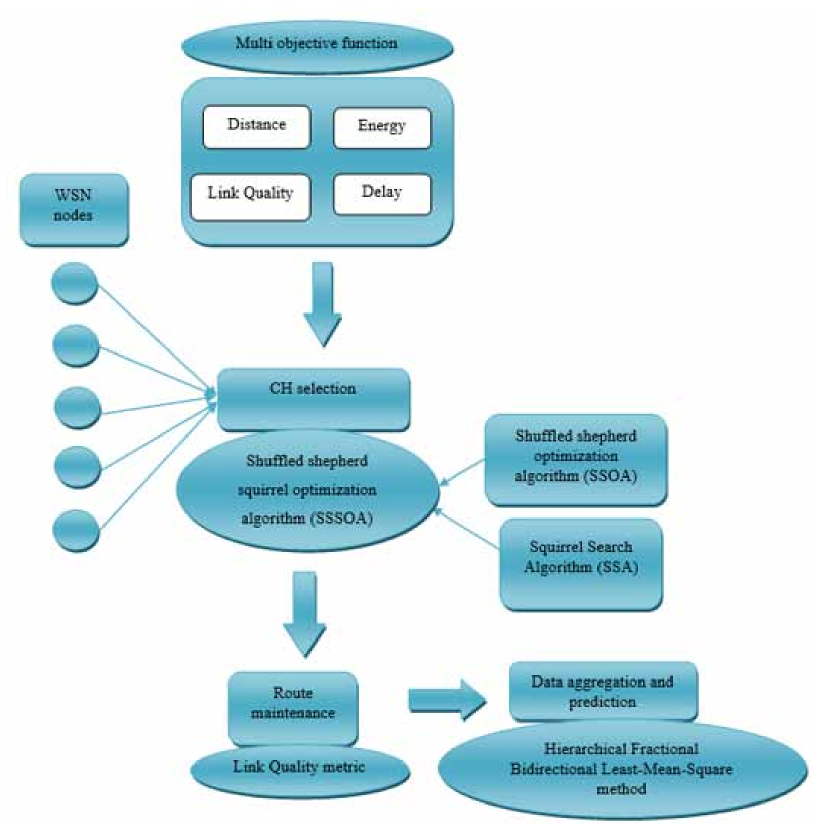
$$L = \frac{-\left(ij + uv\right)\sqrt{\left(i^2 + u^2\right)g^2 - \left(iv - uj\right)^2}}{\left(i^2 + u^2\right)} \tag{8}$$

where, $i = C_O \cos\theta_O - V_P \cos\theta_P$, $j = U_O - V_P$, $u = C_O \operatorname{Sin}\theta_O - V_P \sin\theta_P$, $v = U_O - V_P$.

4. PROPOSED SHUFFLED SHEPHERD SQUIRREL OPTIMIZATION ALGORITHM-BASED IN-NETWORK AGGREGATION IN WIRELESS SENSOR NETWORK

This section illustrates about the proposed SSSOA algorithm-based In-Network Aggregation in WSN. Figure 2indicates block diagram of developedSSSOA-based In-Network Aggregation in WSN. At first, WSN is initialized and CHS process from various nodes is performed. The CH is selected using the developed optimization technique, named as SSSOA. The proposed SSSOA is newly developed by integrating SSA (Jain, *et al*., 2019) and SSOA (Kaveh and Zaerreza, 2020). After that, path with lowest distance is chosen as optimal path and it is selected by multi objective functions, namely delay, distance, link quality and energy. Once optimal path is chosen, then route maintenance is executed in simulated IoT network based on link quality metric. Finally, data aggregation and prediction is processed using HFBLMS (Ganjewar, *et al*., 2018).

Figure 2. Block diagram of proposed SSSOA-based in-network aggregation in WSN



4.1 Cluster Head Selection Based on Shuffled Shepherd Squirrel Optimization Algorithm

Here, SSSOA is developed by for In-Network Aggregation in WSN in which the CHS is processed using developed SSSOA. The developed SSSOA is designed by combining SSOA (Kaveh and Zaerreza, 2020) and SSA (Jain, *et al*., 2019). The SSOA is inspired by shepherd to introduce new multi-community. Initially, the agents are divided into various neighbourhoods and optimization is inspired through shepherd's activity on every neighbourhood. In this method, attention is provided to good and bad agents, which directs to enhance the performance of algorithmic. Additionally, it balances for identifying best computation cost for increasing coverage speed. This SSOA identifies the optimal solution with minimum amount of analysis. On the other hand, SSA is motivated form salps swarming activity while navigating and foraging in oceans. This technique improves random solution in an efficient way. In addition, this algorithm generates optimal solution with high convergence. Furthermore, this method effectively identifies global optima for various uni-modals and multi-modal complex benchmark functions. However, this method is not effective for solving multi objective problems with unfamiliar search spaces. Therefore, SSA is combined with SSOA for obtaining better algorithmic performance.

a) Solution Encoding

The solution vector is used for identifying solution with regards to developed approach. The solution vector includes nodes and CH for selecting CH. Let us assume the CH, and it is denoted as Z in which CHs are selected using the nodes s. The optimal CHs are selected for further processing from node s. In addition, index of CH is signified as T and it ranges from $1 \le s \le T$. The solution encoding of developed methodis showed in figure 3.

Figure 3. Solution encoding

b) Fitness Function Formation

The fitness function is estimated from solution set to identify the optimal solution. Here, fitness function is generated using several parameters, namely energy, delay distance and Percentage of Route Life Time (RLT). The fitness function of developed SSSOA technique is represented by,

$$F_f = \frac{1}{4 \cdot Z_q} \sum_{s=1}^{K_q} E_e + \left(1 - DT_s\right) + \left(1 - DE_s\right) + PR_s \tag{9}$$

where, Z_q specifies number of CH, E_e denotes energy, DT_s represents distance, DE_s signifies delay and R_s indicates percentage RLT.

1) *Energy*: The updated energy model of developed method is illustrated in equation (6) and (7).
2) *Distance:* The distance estimated among cluster head and node is described as below,

$$DT_s = \frac{1}{H_C \cdot Z_q \cdot X} \sum_{y=1}^{C} \sum_{z=1}^{X} \mathrm{E}\left(J_y, J_z\right) \tag{10}$$

3) *Delay:* The delay parameter is calculated using below equation,

$$DE_s = \left(\frac{X_y}{X}\right) \tag{11}$$

4) *Percentage of Route Life Time:* The RLT is defined as leastLLT along with routing path as well as RLT is identical to smallest LLT for the route. Hence, percentage RLT is estimated using below equation,

$$PR_s = \frac{R_s}{L} \tag{12}$$

c) Algorithmic Process of Developed SSSOA

The algorithmic procedure of proposed SSSOA is illustrated in this section.

1) Initialization

Originally, the developed SSSOA begins the solution space for identifying optimal CH, and it is illustrated as,

$$W = \left\{W_1, W_2, \ldots, W_s, \ldots W_t\right\} \tag{13}$$

where, A_t denotes t^{th} population of developed SSSOA.

2) Fitness Function Estimation

Once initialization is done then, fitness function is estimated for every solution by multi objective fitness parameters, namely distance, percentage of RLT, energy and delay. Besides, fitness function is calculated by equation (9).

3) Update Solution Based on Proposed SSSOA

After the estimation of fitness function, the solution is updated using developed SSSOA.The standard equation of SSOA is given by,

$$W_{fg}^{\hat{a}+1} = \gamma \times rand \circ \left(W_{hg}^{\hat{a}} - W_{fg}^{\hat{a}}\right) + \chi \times rand \circ \left(W_{hg}^{\hat{a}} - W_{fg}^{\hat{a}}\right) \tag{14}$$

$$W_{fg}^{\hat{a}+1} = \gamma \times rand \circ W_{hg}^{\hat{a}} - \gamma \times rand \circ W_{fg}^{\hat{a}} + \chi \times rand \circ W_{hg}^{\hat{a}} - \chi \times rand \circ W_{fg}^{\hat{a}} \tag{15}$$

$$W_{fg}^{\hat{a}+1} = -W_{fg}^{\hat{a}} \left(\gamma + \chi\right) rand \circ + \gamma \times rand \circ W_{hg}^{\hat{a}} + \chi \times rand \circ W_{hg}^{\hat{a}} \tag{16}$$

$$W_{fg}^{\hat{a}+1} = \left(\gamma + \chi\right) rand \circ \times W_{hg}^{\hat{a}} - \left(\gamma + \chi\right) rand \circ \times W_{fg}^{\hat{a}} \tag{17}$$

The standard equation of SSA is given below,

$$W_{fg}^{\hat{a}+1} = W_{fg}^{\hat{a}} + \mathrm{H}_{\tilde{x}} \times G_{\tilde{y}} \times \left(W_{rg}^{\hat{a}} - W_{fg}^{\hat{a}}\right) \tag{18}$$

$$W_{fg}^{\hat{a}+1} = W_{fg}^{\hat{a}} + \mathrm{H}_{\tilde{x}} \times G_{\hat{y}} \times W_{rg}^{\hat{a}} - \mathrm{H}_{\tilde{x}} \times G_{\tilde{y}} \times W_{fg}^{\hat{a}} \tag{19}$$

$$W_{fg}^{\hat{a}+1} = W_{fg}^{\hat{a}} \left(1 - \mathrm{H}_{\tilde{x}} \times G_{\tilde{y}}\right) + H_{\tilde{x}} \times G_{\tilde{y}} \times W_{rg}^{\hat{a}} \tag{20}$$

$$W_{fg}^{\hat{a}} \left(1 - \mathrm{H}_{\tilde{x}} \times G_{\tilde{y}}\right) = W_{fg}^{\hat{a}+1} - \mathrm{H}_{\tilde{x}} \times G_{\tilde{y}} \times W_{rg}^{\hat{a}} \tag{21}$$

$$W_{fg}^{\hat{a}} = \frac{W_{fg}^{\hat{a}+1} - \mathrm{H}_{\tilde{x}} \times G_{\tilde{y}} \times W_{rg}^{\hat{a}}}{\left(1 - \mathrm{H}_{\tilde{x}} \times G_{\tilde{y}}\right)} \tag{22}$$

Substitute equation (22) in (17),

$$W_{fg}^{\hat{a}+1} = \left(\gamma + \chi\right) rand \circ W_{hg}^{\hat{a}} - \left(\gamma + \chi\right) rand \circ \left[\frac{W_{fg}^{\hat{a}+1} - \mathrm{H}_{\tilde{x}} G_{\tilde{y}} \times W_{rg}^{\hat{a}}}{1 - H_{\tilde{x}} \times G_{\tilde{y}}}\right] \tag{23}$$

$$W_{fg}^{\hat{a}+1} + \frac{\left(\gamma + \chi\right) rand \circ W_{fg}^{\hat{a}+1}}{1 - \mathrm{H}_{\tilde{x}} G_{\tilde{y}}} = \left(\gamma + \chi\right) rand \circ W_{hg}^{\hat{a}} - \left(\gamma + \chi\right) rand \circ \frac{\left[-\mathrm{H}_{\tilde{x}} G_{\tilde{y}} \times W_{rg}^{\hat{a}}\right]}{1 - \mathrm{H}_{\tilde{x}} \times G_{\tilde{y}}} \tag{24}$$

$$\frac{W_{fg}^{\hat{a}+1}\left(1-\mathrm{H}_{\tilde{x}}G_{\tilde{y}}+\left(\gamma+\chi\right)rand\circ W_{fg}^{\hat{a}+1}\right)}{\left(1-\mathrm{H}_{\tilde{x}}\times G_{\tilde{y}}\right)}=\left(\gamma+\chi\right)rand\circ W_{hg}^{\hat{a}}-\left(\gamma+\chi\right)rand\circ\left[\frac{-\mathrm{H}_{\tilde{x}}\times G_{\tilde{y}}\times W_{rg}^{\hat{a}}}{1-\mathrm{H}_{\tilde{x}}\times G_{\tilde{y}}}\right] \tag{25}$$

$$W_{fg}^{\hat{a}+1}\left[\frac{\left(1-\mathrm{H}_{\tilde{x}}G_{\tilde{y}}\right)+\left(\gamma+\chi\right)rand}{\left(1-\mathrm{H}_{\tilde{x}}\times G_{\tilde{y}}\right)}\right]=\left(\gamma+\chi\right)rand\circ W_{hg}^{\hat{a}}-\left(\gamma+\chi\right)rand\circ\left[\frac{-\mathrm{H}_{\tilde{x}}\times G_{\tilde{y}}\times W_{rg}^{\hat{a}}}{1-\mathrm{H}_{\tilde{x}}\times G_{\tilde{y}}}\right] \tag{26}$$

$$W_{fg}^{\hat{a}+1}=\frac{1-\mathrm{H}_{\tilde{x}}\times G_{\tilde{y}}}{\left(1-\mathrm{H}_{\tilde{x}}\times G_{\tilde{y}}\right)+rand\circ\left(\gamma+\chi\right)}\left\{\left(\gamma+\chi\right)rand\circ W_{hg}^{\hat{a}}-\left(\gamma+\chi\right)rand\circ\left[\frac{-\mathrm{H}_{\tilde{x}}\times G_{\tilde{y}}\times W_{rg}^{\hat{a}}}{\left(1-\mathrm{H}_{\tilde{x}}\times G_{\tilde{y}}\right)}\right]\right\} \tag{27}$$

where, $rand$ describes the random vector, which specifies every element in an interval $\left[0,1\right]$, $\circ$ denotes the element by element multiplication, γ, χ are parameters, $\mathrm{H}_{\tilde{x}}$ represents random gliding distance and $G_{\tilde{y}}$ signifies gliding constant.

4) Step Size Calculation

In every group, shepherd directs the sheep to horse and sheep's are arranged based on their objective function values in rising order. The sheep get chosen from first sheep to final one as well as movement of sheep and selected members are taken as shepherd to calculate step size. Apparently, there are several best sheep and bad sheep, when compared to shepherd. The best sheep is named as horse and hence, there are various horses and sheep for every shepherd. In addition, vector for movement is obtained by nature rule and shepherd directs to horse in nature. Consequently, one of a horses and sheep from residual sheep are randomly chosen. The first sheep goes towards the chosen sheep and for directing sheep shift towards horse. The step size of for each population is computed using equation (14).

5) Estimate Temple Solution Vector

Once step size for every sheep in the herd is computed, then temple vector solution is estimated for every sheep. The temple solution vector is computes by below equation,

$$w_{fg}^{tem}=W_{fg}^{old}+W_{fg}^{\hat{a}+1} \tag{28}$$

6) Update Merge and Agent

If temple objective function is better than old objective function, then location of sheep is updated and combined with herds, Therefore, $W_{fg}^{new} = W_{fg}^{tem}$, or else $W_{fg}^{new} = W_{fg}^{old}$.

7) Update Parameters

γ parameter is equivalent to γ_0 in initial stage of technique then, reducesthrough iteration amount of approach is equal to zero and it is estimated using the equation as follows,

$$\gamma = \gamma 0 - \frac{\gamma_0}{\max iteration} \times iteration \tag{29}$$

χ parameter is identical to χ_0 in beginning if algorithm then, enhancesthrough iteration quantity of algorithm is to $\chi_{\max}$. χ is estimated using below equation,

$$\chi = \chi_0 + \frac{\chi_{\max} - \chi_0}{\max iteration} \times iteration \tag{30}$$

Therefore, decrement in γ and increment in χ slowly reduces exploration and improvesthe development of technique.

8) Termination

Finally, step (3) and (7) are repetitive until particular highest amount of iteration are achieved.

Algorithm 1. Pseudo code of developed SSSOA

Sl. No.	Pseudo code of developed Taylor-TSA based GAN
1	**Input: Population Size**
2	**Output:** $W_{fg}^{\hat{a}+1}$
3	Begin
4	Initialize the problem and define parameters
5	Evaluate the set of elements
6	Sort the set of elements by fitness function based on equation (9)
7	Generate step size matrix
8	Update the parameters using equation (27)
9	Evaluate new set of elements using fitness function
10	Replace best solution
11	End

4.2 Route Maintenance Monitoring

The route maintenance is mainly depends on link quality metrics. If the route life time is fewer than threshold value $\left(R_s < T\right)$, then change a cluster centroid for ensuring route quality.

4.3 Data Aggregation and Prediction using Hierarchical Fractional Bidirectional Least-Mean-Square Method

This section describes the data aggregation and reduction using introduced prediction method, termed as HFBLMS. The developed HFBLMS approach includes two alternations in bidirectional computation by BLMS and weight update using FC in HLMS. The initial weights of technique are supposed as zero in this method. The data gathered from sensor node is transferred to sink node at recurrent time limit in network model. The data's, which are varies from actual data is replaced, whereas computed error go beyondhighest error, termed as $\tilde{e}_{\max}$.

Let us assume the sensor node, which senses a analysis $\tilde{s}(\overline{p})$ at themoment and transfers a series of data, $\tilde{S}\left(\overline{p}\right) = \left\{\tilde{s}\left(\overline{p}-1\right), \tilde{s}\left(\overline{p}-2\right), \ldots, \tilde{s}\left(\overline{p}-\overline{f}\right)\right\}$ to sink node. The node and base station estimated output $\tilde{o}\left(\overline{p}\right)$ error as, $\tilde{e}\left(\overline{p}\right) = \tilde{d}\left(\overline{p}\right) - \tilde{o}\left(\overline{p}\right)$ describes the desired output at time $\overline{p}$. The node chooses whether to transfer sensed data $\tilde{s}\left(\overline{p}\right)$ by comparing $\tilde{e}\left(\overline{p}\right)$ with $\tilde{e}_{\max}$. If attained error is bigger than highest error, then sensor node changes a sensed value with calculated value and transfers data sequence to base station. In some other cases, data transmission does not occur hence, forecasted output is named as recorded data. When, $\tilde{e}\left(\overline{p}\right) \leq \tilde{e}_{\max}$, data sensed by a node is measured as final output, eradicatingcomputed output $\tilde{o}\left(\overline{p}\right)$. The required data $\tilde{d}\left(\overline{p}\right)$ at time $\overline{p}$ is not similar to $\tilde{s}\left(\overline{p}\right)$. Similarly, for same prediction, $\tilde{e}\left(\overline{p}\right) \leq \tilde{e}_{\max}$, data reordered at time $\overline{p}-1$ denoted as $\tilde{s}\left(\overline{p}-1\right)$ is becomes as desired data. Therefore, error computation at time $\overline{p}$ is denoted as $\tilde{e}\left(\overline{p}\right) = \tilde{s}\left(\overline{p}-1\right) - \tilde{o}\left(\overline{p}\right)$. After that, data series at time $\left(\overline{p}+1\right)$ has $\tilde{o}\left(\overline{p}\right)$ as its first element. When, base station accepts data from sensor node then, required output is identical to sensed data. Therefore, data series at period $\left(\overline{p}-1\right)$ is illustrated as, $\tilde{S}\left(\overline{p}-1\right) = \left\{\tilde{s}\left(\overline{p}\right), \tilde{s}\left(\overline{p}-1\right), \ldots, \tilde{s}\left(\overline{p}-\overline{d}-\overline{f}\right)\right\}$. When, $\tilde{e}_{\max}$ is small it increases efficiency of reduction whereas, in large condition it improves accuracy. Therefore, the value which is either too small or too huge is selected.

HLMS (Tan and Wu, 2015) offers fast convergence because of two major reasons, like small length size of filters and reduced Eigen values of correlation matrices. Moreover, HFBLMS method is enhanced by FC (Bhaladhare and Jinwala, 2014) in weight update procedure. In addition, BLMS (Yapıcı and Yılmaz, 2012) method is combined in HLMS for enhancing prediction performance, since this technique offers both backward and forward direction evaluation. The integration of BLMS and FC in HLMS prediction technique is utilized to enhance the data transmission performance with data prediction for data reduction.

5. RESULTS AND DISCUSSION

This section illustrates about outcomes and discussion of devisedSSSOA approach based on the performance metrics, likeamount of alive nodes, data packet delivery rate, energy, prediction error and delay.

5.1 Experimental Setup

The implementation of devised SSSOAmethod is performed in NS2 tool with UBUNTU software and 8GB RAM.

5.2 Performance Metrics

The performance evaluated for developed SSSOA method includes, delay, number of alive nodes, energy, prediction error and data packet delivery rate.

The delay and energy parameter is explained in above section and delay is computed using equation (11) also energy is estimated based on equation (6) and (7).

5.2.1 Number of Alive Nodes

Alive nodes are specified as quantity of nodes, itconvertsthe data to base station after integrated data. Alive nodes are usedfor computing weights of random numbers.

5.2.2 Prediction Error

The prediction error is termed as stoppage of severalnormal event to occur and it is expressed as,

$$\mathrm{P}_{\mathrm{E}} = \frac{\mathrm{M}_{V} - \mathrm{K}_{V}}{\mathrm{M}_{V}} \times 100 \tag{31}$$

where, M_{V} specified measured value and K_{V} denotes predicted value.

5.2.3 Data Packet Delivery Rate

PDR is exposed as ratio of received data packets and sent data packets is also it is employed to calculateefficiency of routing.

$$PDR = \frac{\mathrm{Re}\,ceived\ \ data\ \ packets}{Sent\,data\ \ packets} \tag{32}$$

5.3 Experimental Results

The simulation output of proposed SSSOA technique using 75 nodes are displayed in figure 4. Here, the green, blue, yellow, brown, black and rose circles specified the cluster nodes, and cluster head nodes, source and destination nodes are exposed.

5.4 Comparative Methods

The existing methods, like DRINA (Villas, *et al*., 2012), HFBLMS (Ganjewar, *et al*., 2018), TF-SCR (Nisha and Basha, 2020) and SSOA (Kaveh and Zaerreza, 2020) are analysed with 75 and 100 nodes for comparison with developed SSSOA.

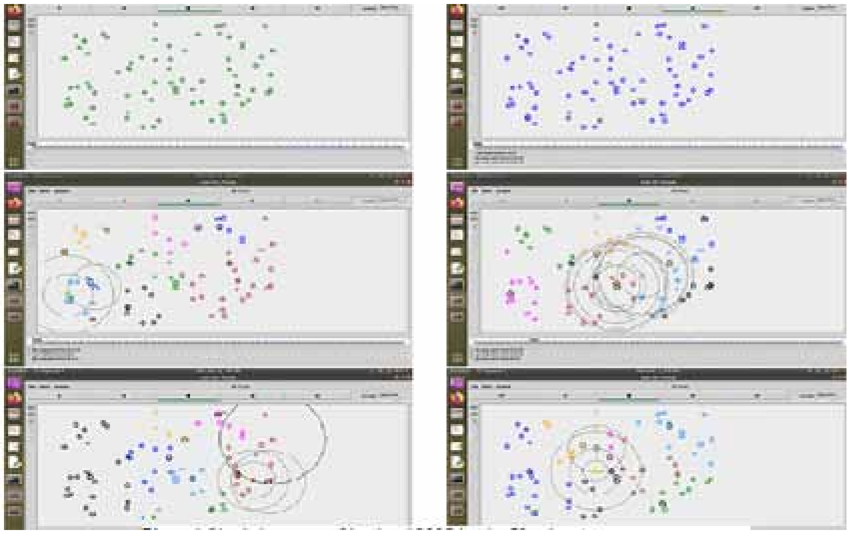
5.5 Comparative Analysis

This section elaborates about comparative analysis of developed SSSOAbased on 75 nodes and 100 nodes.

a) Comparative Analysis with Respect to 75 Nodes

The analysis with respect to number of alive nodes, delay, energy, prediction error and PDR for 75 nodes by changing 0 to 100 roundsis expressed in figure 5. The analysis with regards to number of alive nodes through varying the rounds from 0 to 100 is showed in figure 5 a). In 68th round, quantity of alive nodes estimated by present methods, like DRINA, HFBLMS, TF-SCR and SSOA are 37, 19, 0 and 68, while the developed SSSOA method attains 75. The analysis based on delay parameter is

Figure 4. Simulation output of developed SSSOA using 75 nodes.

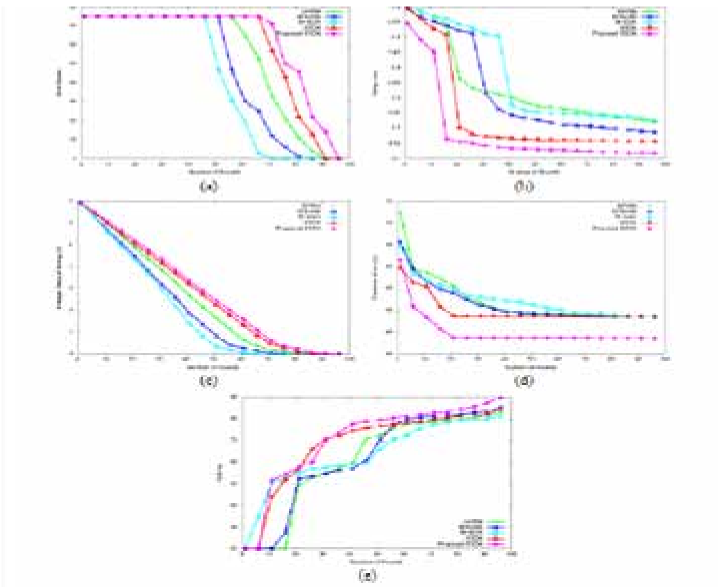


specified in figure 5 b). At 68th round, delay obtained by existing techniques, like DRINA, HFBLMS, TF-SCR, SSOA and developed SSSOA method are 0.255sec, 0.208sec, 0.244sec, 0.159sec and 0.125sec. Moreover, the analysis using energy parameter is represented in figure 5 c). At the round of 50, energy values estimated by existing DRINA, HFBLMS, TF-SCR and SSOA are 1.77J, 0.944J, 0.419J, 2.36J, while developed SSSOA method is 2.55J. In addition, analysis based on prediction error is portrayed in figure 5 d). For round number 68, prediction error obtained by present DRINA, HFBLMS, TF-SCR and SSOA are 49.03%, 48.88%, 49.42%, 48.65%, while developed SSSOA technique obtains the prediction error value of 43.63%. Along with this, percentage improvement of developed approach for prediction error with existing DRINA, HFBLMS, TF-SCR and SSOA are 11.01%, 10.74%, 11.71% and 10.31%. In addition, figure 5 e) signifies the analysis of PDR through changing amount of rounds. At 68th round, the PDR value computed by existing DRINA, HFBLMS, TF-SCR, SSOA and developed SSSOA are 78.13%, 80.75%, 76.52%, 79.14% and 82.24%. The percentage improvement of developed SSSOA approach, when compared with other techniques, like DRINA, HFBLMS, TF-SCR, SSOA are 4.99%, 1.80%, 6.94% and 3.76%.

b) Comparative Analysis based on 100 Nodes

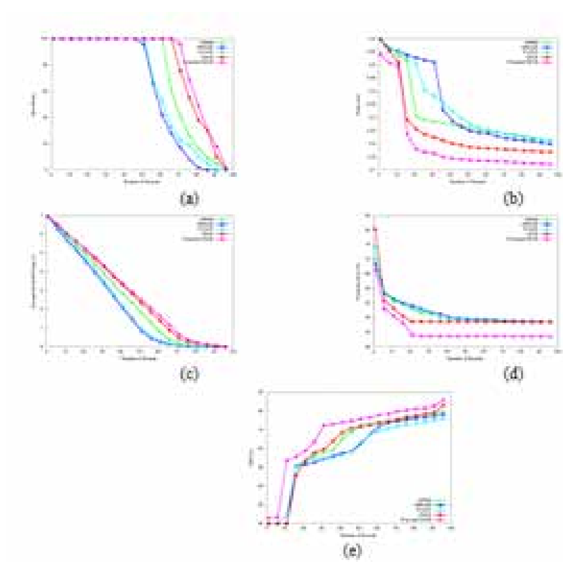
The analysis with respect to number of alive nodes, delay, energy, prediction error and PDR for 75 nodes by changing 0 to 100 rounds is expressed in figure 6. The analysis with regards to number of alive nodes through varying the rounds from 0 to 100 is showed in figure 6 a). In 68th round, quantity of alive nodes estimated by present methods, like DRINA, HFBLMS, TF-SCR and SSOA are 37, 19, 0 and 68, while the developed SSSOA method attains 75. The analysis based on delay parameter is specified in figure 6 b). At 68th round, delay obtained by existing techniques, like DRINA, HFBLMS, TF-SCR, SSOA and developed SSSOA method are 0.255sec, 0.208sec, 0.244sec, 0.159sec and 0.125sec. Moreover, the analysis using energy parameter is represented in figure 6 c). At the round of 50, energy values estimated by existing DRINA, HFBLMS, TF-SCR and SSOA are 1.77J, 0.944J, 0.419J, 2.36J, while developed SSSOA method is 2.55J. In addition, analysis based on prediction error is portrayed in figure 6 d). For round number 68, prediction error obtained by present DRINA, HFBLMS, TF-SCR and SSOA are 49.03%, 48.88%, 49.42%, 48.65%, while developed SSSOA technique obtains the prediction error value of 43.63%. Along with this, percentage

Figure 5. Comparative analysis of developed SSSOA using 75 nodes through varying amount of rounds, a) quantity of alive nodes, b) delay, c) energy, d) prediction error and e) data packet delivery rate



improvement of developed approach for prediction error with existing DRINA, HFBLMS, TF-SCR and SSOA are 11.01%, 10.74%, 11.71% and 10.31%. In addition, figure 6 e) shows the analysis of PDR by changingamount of rounds. At 68th round, PDR value computed through existing DRINA, HFBLMS, TF-SCR, SSOA and developed SSSOA are 78.13%, 80.75%, 76.52%, 79.14% and 82.24%. The percentage improvement of developed SSSOA approach, when compared with other techniques, like DRINA, HFBLMS, TF-SCR, SSOA are 4.99%, 1.80%, 6.94% and 3.76%.

Figure 6. Comparative analysis of developed SSSOA using 100 nodes through changing quantity of rounds, a) quantity of alive nodes, b) delay, c) energy, d) prediction error and e) data packet delivery rate



5.6 Comparative Discussion

The comparative analysis of various existing method and proposed technique are expressed in this section. Table 1 illustrates the comparative discussion with respect to alive nodes, delay, energy, PDR and prediction error. The developed SSSOA technique attained high number of alive nodes of 100 however, other existing DRINA, HFBLMS, TF-SCR and SSOA techniques attains 42, 18, 26 and 84 for 100 nodes. Similarly, the developed SSSOA method obtains less delay of 0.132sec for 100 nodes, while existing approaches, like DRINA, HFBLMS, TF-SCR and SSOA are 0.239sec, 0.221 sec, 0.239sec and 0.178sec. Moreover, the developed SSSOA scheme achieves high energy 0.762J and high PDR of 79.84% for 100 nodes. The prediction error obtained by existing methods, such as DRINA, HFBLMS, TF-SCR and SSOA are 48.84%, 49.04%, 48.80% and 48.64%, but the developed SSSOA obtains less prediction error of 43.65%.

Table 1. Comparative analysis

Nodes/ Methods	Metrics	DRINA	HFBLMS	TF-SCR	SSOA	Proposed SSSOA
75 nodes	**Alive nodes**	33	15	0	57	**75**
	Delay (sec)	0.252	0.206	0.244	0.158	**0.124**
	Energy (J)	0.211	0.052	0	0.507	**0.706**
	Prediction Error (%)	49.01	48.85	49.37	48.64	**43.62**
	Data packet delivery rate (%)	78.55	81.07	77.51	79.50	**82.67**
100 nodes	**Alive nodes**	42	18	26	84	**100**
	Delay (sec)	0.239	0.221	0.239	0.178	**0.132**
	Energy (J)	0.251	0.066	0.095	0.511	**0.762**
	Prediction Error (%)	48.84	49.04	48.80	48.64	**43.65**
	Data packet delivery rate (%)	75.56	74.74	71.71	75.37	**79.84**

6. CONCLUSION

The method, named as SSSOA approach is devised in this papers for In-network aggregation in WSN. In WSN, the path is created from source node to destination by routing process and source node transmits a packet to destination. At first, WSN is initiated and appropriate CH is chosen from every nodes. In this scheme, CH is selected with respect to developed SSSOA. The developed SSSOA is devised through integrating SSA and SSOA. Once the CH is selected, lowest distance path is chosen as optimal path and it is selected using multi objective functions, such as delay, energy, distance and link quality. After the optimal path selection, route maintenance procedure is executed in a simulated network based on link quality. Once route maintenance is completed, data reduction and data aggregation is carried out based on HFBLMS. Furthermore, performance of developed SSSOA is compared with several performance metrics, such as energy, delay, PDR, prediction error and alive node. The developed SSSOA achieves high alive node of 100, high energy of 0.762J and high PDR of 79.84% and it obtains less delay of 0.132sec and less prediction error of 43.65%. In future, more analysis will be performed and also more metrics will be included for computing the efficiency of proposed method.

CONFLICTS OF INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

Funding Statement

No funding was received for this work.

Process Dates:

Received: May 18, 2021, Revision: October 25, 2021, Accepted: August 6, 2022

Corresponding Author:

Correspondence should be addressed to Rajesh L., lrajeshl333@gmail.com]

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