Intelligent Framework Using IoT-Based WSNs for Wildfire Detection

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ABSTRACT IoT-based WSNs have proved their significance in delivering critical information pertaining to hostile applications such as Wildfire Detection (WD) with the least possible delay. However, the sensor nodes deployed in such networks suffer from the perturbing concern of limited energy resources, restricting their potential in the successful detection of wildfire. To extenuate this concern, we propose an intelligent framework, Sleep scheduling-based Energy Optimized Framework (SEOF), that works in two folds. Firstly, we propose an energy-efficient Cluster Head (CH) selection employing a recently developed meta-heuristic method, Tunicate Swarm Algorithm (TSA), that optimizes the five novel fitness parameters by integrating them into its weighted fitness function. Secondly, we perform a sleep scheduling of closely-located sensor nodes based on the distance threshold calculated through a set of experiments. Sleep scheduling methodology plays a pivotal role in abating the number of data transmissions in SEOF. Finally, we simulate SEOF in MATLAB under different scenarios to examine its efficacy for the various performance metrics and scalability features. Our empirical results prove that SEOF has ameliorated the network stability period for two different scenarios of network parameters by 35.3% and 216% vis-à-vis CIRP.

INDEX TERMS Cluster head (CH), energy efficiency, IoT-based WSN, sleep scheduling, tunicate swarm algorithm (TSA), wildfire detection (WD).

I. INTRODUCTION

With the evolution of sensing technology, IoT-based WSNs have been proliferating in handling multifaceted applications [1]. IoT-based sensor nodes play a pivotal role in disseminating information from hostile areas where human's intervention is quixotic [2]–[4]. The sensed information is gathered from these hostile areas and then forwarded to the sink from where it is sent to the user for performing the required course of action [5]. There is an enormous number of applications of IoT-based Wireless Sensor Network (WSN), and among them, one predominantly prevalent is the Wildfire Detection (WD) [6], [7]. Wildfires are a recurrent phenomena around the world. Millions of forest hectares are burnt in flames from wildfires every year [8]. The Global Forest Watch (GFW)

reports fire statistics of any country, and it also presents the status of fire alarms for different regions [9]. The Mendocino Complex Fire loomed up in Northern California on July 27th, 2018 was registered as the largest fire in the history that burnt 459,123 acres of land. According to a report by Forest Survey of India (FSI), occasional fires occur to the 54.40% of forests in India and 7.49% of forest experience moderately frequent fires [10]. Basically, the 90% forest fires are caused by the anthropogenic activities namely, unattended campfire, smoking, burning debris, firework, poachers and timber mafia, etc. The remaining 10% are caused due to the natural phenomenon namely, lightening, volcanic eruption, and due to meteorites, etc. The forest fires are mostly dependent upon the type of vegetation or trees grown in the forest areas. Pine tree forests are highly fire prone as the leaves/needles of pine act as a fuel for forest fires due to its resin content [11]. Therefore, many significant attempts are reported to

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replace the pine trees with other suitable trees that grows broad-leaves [12].

According to the National Fire Danger Rating System (NFDRS), firefighters must be made aware at a maximum of six minutes after the fire is started, to curb it, before it spreads to a large scale [13]. Therefore, it can be concluded that there is a great significance of early detection of wildfires to avoid the high magnitude of loss to the property, lives, flora and fauna. Since the advancements in Micro-Electro-Mechanical-System (MEMS), the various researchers have worked to pact with WD through multiple imaging patterns or the use of sensors. It is evident that the former method fails in adverse environmental conditions. Therefore, we use the latter approach for WD while considering the energy efficiency of the IoT-based sensor nodes. In our proposed work, four Data Collecting Sinks (DCS) are placed outside the network to deliver the fire related information with the least delay. The placement of four DCS avoids the hot-spot problem and assists in ameliorating the network lifetime [14].

Further, to resolve the issues of WD, energy-efficient routing is required that must immunizes the network from the hot-spot problem and also delivers critical information with least delay. Multitudinous attempts are reported so far that address the above said concern by optimizing the cluster-based routing which incorporates significant parameters for Cluster Head (CH) selection [15]. However, routing strategies that optimize clustering by employing optimization technique with high exploration and fast convergence are still left unnoticed. To resolve this concern, we use Tunicate Swarm Algorithm (TSA) that possesses high exploration and exploitation capabilities, and due to such remarkable features, it has high convergence [16]. TSA is tested on different benchmarks, and it is revealed through its statistical outcomes that it is more efficient than the competitive algorithms. A detailed study about TSA can be done from study [16].

The other crucial approach in preserving energy of IoT-based sensor nodes is sleep scheduling of these nodes. These nodes when put into sleep state, turn off either the radio (disrupting communication capability) or sensory device (halting the sensing/detection of events) [17]. Sleep scheduling must be examined with prudence and random sleep scheduling is not encouraged due to its repercussion on network connectivity and topological efficiency. A profusion of sleep scheduling mechanisms are discussed in detail by the various researchers [18], [19]. However, none of the study considered the joint consideration of two crucial aspects; sleep scheduling and energy efficient CH selection.

A. RESEARCH CONTRIBUTIONS
To address the concern of WD with energy optimized clustering and sleep scheduling, we state our contributions as follow.

1) We propose an intelligent framework named as Sleep scheduling-based Energy Optimized Framework (SEOF) pertinent to WD that uses IoT-based sensor nodes. In SEOF, we optimize the CH selection using
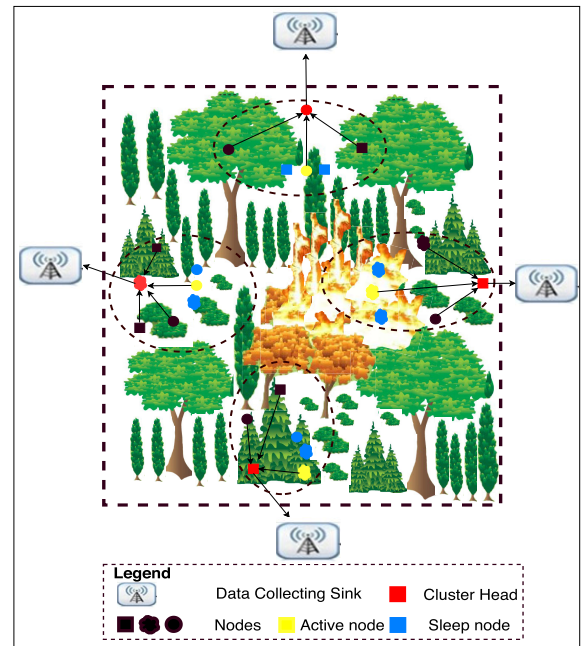

FIGURE 1. The proposed scenario of SEOF.

a meta-heuristic optimization method named TSA [16]. We consider five essential parameters for selecting CH, which are optimized in the integrated fitness function of TSA. These parameters include distance between the DCS and the node, node proximity, network's average energy, residual energy and time delay.

2) We apply sleep scheduling mechanism in each cluster, just before the start of intra-cluster data transmission. As nodes are randomly deployed, we consider distance and energy level of adjacent nodes to put them into sleep or active state. If the distance among the adjacent nodes is lower than the threshold distance, then only one node is made active which transfers the data to CH until it sustains.

3) We employ four DCS around the network periphery to extenuate the concern of hot-spot problem and early data delivery to a sink in large area networks. Consequently, it eradicates the aforementioned problem by introducing single-hop communication between the sensor nodes and the DCS. Figure 1 shows the proposed scenario for WD.

4) We perform extensive simulation analysis for two different scenarios (Case I and Case II) to examine the performance and scalalability. These cases have different network dimensions including the count of nodes deployed and area of network. We use several crucial performance metrics that include stability period, network survival period, network's remaining energy and throughput to evaluate the efficacy of SEOF.

This is the first ever work for WD that incorporates multiple DCS to immune the network from the hot-spot problem, and expedite the data delivery through optimized CH selection. In addition to this, it is the first instance when the

joint consideration of sleep scheduling and energy efficient clustering pertinent to WD is taken into account.

The rest of manuscript is structured as follows. Section II addresses the related work for energy-efficient routing techniques, WD and sleep scheduling mechanisms. Further, in Section III, we discuss the operation of TSA and SEOF. Next, in Section IV, we present outcomes and discussions. Finally, Section V concludes and highlights directions for future work.

II. RELATED WORK

The role of IoT in various real-time applications has been unparallel to any other technology [20]–[26]. Many researchers have targeted Industrial IoT for its efficacy in network performance [27]–[29] however, a comprehensive attention is still required for some hostile applications for an example WD. WD has been one of the challenging tasks to curb the wildfires, which have been the prominent cause behind damaging several hectar [8]. Since the advancements in Micro-Electro-Mechanical-System (MEMS), the various researchers have worked to pact with WD through multiple imaging patterns or sensors. It is evident that the former method fails in adverse environmental conditions. Therefore, we use the latter approach for WD while considering the energy efficiency of the 5G-Integrated IoT-based sensor nodes. Further, we briefly discuss the related work targeting WD, CH selection and sleep scheduling in sensor network.

A. WD TECHNIQUES

Cao *et al.* [30] proposed ABi-LSTM for WD which involves a large amount of image capturing and complexities in the installation over the forest cover. Leal *et al.* [31] utilized the onboard fuzzy logic approach for the detection of fire spots in Amazon forest of Brazil. However, the system gets compromised when the environmental conditions get worsened. Aslan *et al.* [32] proposed a general WD framework that works for developing a technique for strategically deploying the sensor nodes. The authors used deterministic deployment of sensor nodes that adds complexity in real time implementation. The authors proposed an architecture for WD and designed a clustering protocol, but it is observed that regular or deterministic sensor nodes deployment adds complexity to the network. Jan *et al.* [33] proposed a Sybil detection approach which employs residual energy and RSSI-based Sybil attack detection strategies. But, it is noted that the choice of CH is computationally expensive, and it further introduces overheads in the proposed algorithm. As a result, this problem ultimately leads to gigantic energy consumption.

The wildfires have been so frequent across the globe, but the promising solution has not come yet into the limelight. It is anticipated that the appropriate CH selection exploited for WD will help in handling this cause efficiently.

It is learnt from the retrospective study that the cluster-based routing mechanism plays a pivotal role in WD [34]. A plethora of attempts for the optimized CH selection are reported in the existing literature. Behera *et al.* [15]

presented CH selection by considering the residual energy solely. Hence, the proposed approach is energy inefficient as the ignorance of the distance factor for CH selection ameliorates the energy consumption. Pokhrel *et al.* [35] projected the Cluster-based Intelligent Routing Protocol (CIRP) that used crucial factors for CH selection to eradicate the hot-spot problem. However, in CIRP, the CH selection did not consider the delay factor involved in delivering the data to the sink. Therefore, it is not suitable for WD application. Verma *et al.* [5] proposed Genetic Algorithm-based Optimized Clustering (GAOC) by considering three factors namely, node density, energy and distance for choosing CH. Furthermore, the Genetic Algorithm (GA) employed for CH selection suffered from slow convergence. Further, Behera *et al.* [36] proposed i-SEP technique in which the choice of CH was based on the threshold value calculated for every type of heterogeneous node. However, the proposed technique did not consider the various other essential parameters, namely node density, network average energy, etc. Sharma *et al.* [37] proposed Energy-efficient Trusted Moth Flame Optimization and Genetic Algorithm (eeTMFOGA) based clustering algorithm, which selects CH based on node density, remaining energy, packet forwarding progress, distance, and delay in transmission. However, there is a significant problem with eeTMFOGA which suppress its pertinence to hostile applications. The sensor nodes and Base Station (BS) are moving, which will bring the high challenges for WD in the context of its real time implementation. Some of the researchers [38], [39] also exploited the fuzzy system for CH selection. The authors in [38] proposed Fuzzy Logic-based Effective Clustering (FLEC) technique but it did not consider the delay factor. In [39], CH selection is done solely based on the RSSI value. Therefore, the scope of these fuzzy-based algorithms is not pertinent to WD. We discern from the literature study that the meta-heuristic methods are more promising as they optimize each factor opted for CH selection to acquire the best possible solution [3], [4], [24], [27]–[29], [40].

1) WHY TSA FOR CH SELECTION?

TSA possesses high exploration and exploitation capabilities, and due to such remarkable features, it has high convergence. TSA is tested on different benchmarks, and it is revealed through its statistical outcomes that it is more efficient than the competitive algorithms. A detailed study about TSA can be done from study [16].

B. SLEEP SCHEDULING METHODS

It is learnt from the various studies related to cluster-based routing mechanism, if the number of participating nodes can be reduced, it can elongate the network lifetime comprehensively. Therefore to address this concern, many researchers have considered sleep scheduling of sensor nodes [41], [42]. The paramount reason behind it is the fact that the adjacent nodes have this propensity to sense similar value of targeted attribute. Hence, keeping only one node in active state till

it has energy, does not harm the network [43], [44]. The authors in [45] proposed an Intelligent Sleep scheduled algorithm (iSleep) that considered the temperature sensitivity of the nodes for taking the decision to put it in active or sleep state. Due to the multi-hop communication, iSleep suffers from hot-spot problem. The sleep scheduling has also played a pivotal role in handling the energy conservation for Wireless Body Area Network (WBAN) [18], [19]. The authors in [44] proposed a hybrid approach considering energy harvesting and non-harvesting nodes to elongate the network lifetime. Due to the added harvesting resources, the proposed approach is costly. The authors in [46] proposed Energy aware Scheduling with Quality Guarantee method (ESQG) that aimed to decrease the count of awakening nodes with the process of information fusion. The authors considered the importance degree for different surveillance locations. The proposed method suffers from high computational overheads. Hence, there is a need of a sleep scheduling mechanism that avoids hot-spot problem and also maintain energy balancing in the network. We addresses this concern by a novel method of sleep scheduling mechanism in SEOF. Further, we explain its operational framework.

III. PROPOSED WORK: SEOF

In this section, the network presumptions and working operation of SEOF are discussed.

A. NETWORK ASSUMPTIONS

We consider some network assumptions while implementing the proposed work.

1) The nature of the network is stationary, i.e., nodes and DCS remain stationary throughout the network run. Three heterogeneous nodes namely, normal, advanced and super nodes are used which have least, intermediate and maximum level of energy, respectively.

2) We assume that DCS has no constraints of energy, computation, and network coverage as long as the operation of SEOF is concerned.

3) Further, we assume our network to be a square-shaped area to use it as a paradigm to perform our simulation.

4) The deployment of IoT-based sensor nodes is done randomly but in a uniform pattern. Each node is location-unaware and is given a unique id once it is deployed. These nodes compute distance between different entities based on Received Signal Strength Indicator (RSSI) value [35].

5) We do not consider the factors of radio interference and any hindrance or signal attenuation due to the presence of physical objects.

6) We consider the proposed protocol to be ideally secured. The security considerations for this work, are out of scope.

7) We have not considered homogeneous nodes due to the fact that existence of homogeneity is not feasible due to different factors that include manufacturing differences, and different period of activation once these nodes are deployed.

B. WORKING STRUCTURE OF SEOF

It functions in two stages namely set-up and steady-state phase [5]. In the former stage, network formation and CH selection are done for the network, whereas the latter involves the process of data transmission during inter-cluster and intra-cluster communication in the network. It is worth noting that we apply sleep scheduling mechanism in each cluster before data transmission is commenced. In Algorithm 1, we mention various steps involved in the working process of SEOF.

1) SET-UP PHASE

This phase pacts with the network formation which involves 'the node deployment and sink placement' and CH selection. We employ four DCS outside the network as illustrated in Figure 1. Then, we deploy heterogeneous IoT-based sensor nodes randomly in the network which is assumed to be a forest cover of pre-defined dimensions. We use TSA to select CH through the mathematical modelling of TSA's fitness function which we discuss in detail as follows.

(a) **Fitness parameters employed in SEOF for CH selection:** We use five essential fitness parameters for the selection of CH. We define symbols with their meanings in Table 1 that are used in proceeding sections. These parameters are discussed as follow:

1) Energy (Residual, initial and threshold value): The first parameter, i.e., F_1 considers residual, initial, and threshold energy of a node for CH selection. It is imperative to consider the updated energy value of the candidate nodes as nodes consume energy in commensurate with a gradual progression of rounds. Equation (1) determines the summation ratio of the residual energy of the ith node to its initial value of energy, multiplied with its threshold energy value. The threshold energy level of a node defines the required energy value of a candidate node for its selection as CH. In this work, the threshold energy is taken as 0.3 Joule after performing a number of experiments. It is noted that higher the value of F_1, the greater the probability of a node for its election as CH.

$$F_1 = \sum_{i=1}^{n} \frac{E_{res}(i)}{E_{in}(i)} \times E_{THD}(i) \quad (1)$$

2) Distance among node and DCS: This fitness parameter called the distance factor is the fundamental factor for any successful wireless communication between two entities [47]. The second fitness parameter i.e., F_2 computes ratio of distance factor. It is the summation ratio of the distance among 'a candidate node and the nearest DCS' and an average distance among all nodes from their nearest DCS. It is noted that a node should have a low value of distance ratio for its selection as CH to preserve its energy.

Algorithm 1 SEOF Algorithm

Input : $n = 100$, R_{max} (Rounds maximum value),
$DCS_1 = (110, 50)$, $DCS_2 = (50, 110)$,
$DCS_3 = (-10, 50)$, $DCS_4 = (50, -10)$

Output: $A = CH\_N$, $dead_{nodes}$, $alive_{nodes}$ and r

1 Deployment of heterogeneous sensor nodes $CH\_N = 0$
2 Initializing CH nodes
3 **for** r *(round) = 1 to* R_{max} **Then**
4    $alive_{nodes} = n$
5    $dead_{nodes} = 0$
6   **for** $i = 1$ *to* n **Then**
7   **if** $E_{res}(i) == 0$ **then**
8        $dead_{nodes} = dead_{nodes} + 1$
9   **if** $dead_{nodes} == 0.9 \times n$ **then**
10          $all\_dead = R_C$ (current value of round)
11   **end if**
12        $alive_{nodes} = alive_{nodes} - dead_{nodes}$
13   **end if**
14   **for** $i = 1$ *to* n **Then**
15   **if** $E_{res}(i) > 0$ **then**
16   Applying TSA for choosing CH
17          $CH\_N = CH\_N + 1$
18   **for** $k = 1$ *to* $(CL - 1)$ **Then**
19   Compute distance of kth to j^{th} node
20   **if** $D_{k-j} < D_{thd}$ **then**
21   **if** $E_{res}(k) > E_{res}(j)$ **then**
22   j^{th} node $\leftarrow Sleep_{state}$
23   **else**
24   k^{th} node $\leftarrow Sleep_{state}$
25   **end if**
26   **else**
27   break
28   **end if**
29   **end for**
30   i^{th} active node $\leftarrow$ Assigning TDMA slot
31          $CH\_N \longleftarrow i^{th}$ active node
32          $Near_{DCS} \longleftarrow CH\_N$
33   Update $E_{res}(i)$ using [47]
34   **else**
35   break
36   **end if**
37   **end for**
38   **if** $dead_{nodes} == 0.9 \times n$ **then**
39   break
40   **end if**
41   **end for**
42 **end for**
43 return A

Equation (2) and equation (3) show the computation of 'distance ratio' and 'average distance of the node from the DCS'. For an energy efficient

TABLE 1. Symbol definition.

Symbols	Meaning
E_{in}	Node's initial energy
E_{res}	Node's residual energy
$E_{THD}(i)$	i^{th} node's threshold energy
n	Total nodes considered
$Davg_{nd-DCS}$	Average distance between all nodes and their nearest DCS
$Dist_{Ratio}$	Ratio of distance factor
$D_{nd-DCS}(i)$	Distance among i^{th} node and the nearest DCS
$Davg_{i-j}$	Distance among i^{th} and j^{th} node
CL	Cluster nodes count
Nd_{pxm}	Node proximity
T_{delay}	Time delay
T_{Ndelay}	Normalized time delay
$T_{delay(i)}$	Time delay of ith node
$T_{delay(min)(i)}$	Minimum time delay of ith node
$T_{delay(max)(i)}$	Maximum time delay of ith node
$\lambda, \delta, \beta, \gamma$ and σ	Variables with equal weight values
$dead_{nodes}$	Number of dead nodes
D_{k-j}	Distance between k^{th} and j^{th} nodes
$alive_{nodes}$	Number of alive nodes
$Near_{DCS}$	Nearest DCS
tx	transmission
R_C	Current round

CH election, a candidate node should have higher value of F_2 as depicted from equation (4).

$$Dist_{Ratio} = \sum_{i=1}^{n} \frac{D_{nd-DCS}(i)}{Davg_{nd-DCS}} \quad (2)$$

$$Davg_{nd-DCS} = \frac{1}{n} \times \sum_{i=1}^{n} D_{nd-DCS}(i) \quad (3)$$

$$F_2 = \frac{1}{Dist_{Ratio}} \quad (4)$$

3) Node proximity: The third fitness parameter i.e, F_3) assists in choosing a node having greater node count around its vicinity as a CH. Consequently, the distance among the cluster member nodes and a candidate node (to be selected as CH), decreases. Equation (5) determines the average distance between the adjacent nodes i.e., i^{th} and j^{th} node in a cluster. Equation (6) illustrates that a node having lowest average distance from the other nodes in the cluster is selected by F_3. In the other words, a node with higher number of neighboring nodes is selected.

$$Nd_{pxm} = \frac{1}{CL} \times \left(\sum_{i=1}^{CL-1} \sum_{j=1}^{CL-1} Davg_{i-j}(i) \right) \quad (5)$$

$$F_3 = \frac{1}{Nd_{pxm}} \quad (6)$$

4) Network's average energy: This parameter, i.e., F_4 considers the network's average energy, which must be considered while selecting a node as a CH. As the data transmission continues, the network's average energy abates which in turn abates the count of a number of CHs to be selected for a particular round. Equation (7) depicts the network's average energy. It is evident that higher the value of F_4 for a candidate node, more chances it will have, to become a CH.

$$F_4 = \frac{1}{n} \times \sum_{i=1}^{n} E_{res(i)} \qquad (7)$$

5) Time Delay: The fifth fitness parameter, i.e., F_5, is one of the significant contributions of presented work due to its direct dependence on curbing the wildfire at the earliest. When the network area is huge and the placement of the sink inside the network is not possible due to the hostile environment, the sensors inevitably follow multi-hop communication. Consequently, the critical fire-alarming information is delivered very late leading to massive damage to the forest covers. Equation (8) computes the time delay from the ratio of distance and speed of the data packet which is assumed to be traveling with the speed of light i.e., c under ideal conditions. Equation (9) normalizes the time delay to limit its value in the range [0 1].

$$T_{delay}(i) = \frac{D_{nd-DCS}(i)}{c} \qquad (8)$$

$$T_{N_{delay}} = \frac{T_{delay}(i) - T_{delay(min)(i)}}{T_{delay(max)(i)} - T_{delay(min)(i)}} \qquad (9)$$

$$F_5 = \frac{1}{T_{N_{delay}}} \qquad (10)$$

In equation (10), the value of F_5 should be maximized to select the node with the least delay involved in transmission of data to the DCS.

(b) **Fitness Function:** The fitness function is the linear combination of the fitness parameters computed above. The fitness function, i.e., F, should be minimized to attain the optimized selection of the node as CH. Equation (11) gives the value of the fitness function, which is processed further in TSA optimization method.

$$F = \frac{1}{\lambda \times F_1 + \delta \times F_2 + \gamma \times F_3 + \beta \times F_4 + \sigma \times F_5} \qquad (11)$$

$$\delta + \lambda + \beta + \gamma + \sigma = 1 \qquad (12)$$

Equation (12) represents a weighted sum of above-mentioned weight factors associated with different fitness parameters.

2) STEADY-STATE PHASE
Once, the CHs are selected in the network, the process of sleep scheduling mechanism in each cluster, is applied in the following steps.

1) In the first step, we compute the distance of a cluster member node with the other nodes in that cluster. If the distance computed among any two nodes is lower than the threshold distance (we define it through multiple simulations as given in Figure 5 (c)), then those two nodes are considered further for energy checking.
2) In the second step, we check the current energy value of those two nodes selected from the first step, and the node with lesser energy from the other, enters into sleep state whereas other stays active until it sustains.
3) In the third step, as soon as the active node drains its energy, the node with sleep state is triggered to active state.

The whole process of operation of SEOF including the sleep scheduling mechanism, is explained in the Algorithm 1. The CH gathers, aggregates and then forwards the information to the nearest DCS.

C. DESCRIPTION FOR ALGORITHM 1
We present the operational framework of SEOF in Algorithm 1. The detail description of this algorithm is given as follows. We consider the network dimensions as an input to the algorithm. It include number of nodes, maximum number of rounds i.e., R_{max} for which the algorithm has to run, and the Cartesian coordinates which define the location of the four DCS placed outside the network. In output of this algorithm, we get the selected CH by applying TSA optimization method, the dead and alive nodes status with the respect to round, the final value of round when the algorithm is halted. We delineate the whole process covered by SEOF in Algorithm 1 as follows.

In **Line 1**, we deploy heterogeneous sensor nodes and placement of DCS is done. In **Line 2**, we initialize the CH_N variable to store the count of CHs. In **Line 3-Line 42**, we explain the whole process of SEOF with the steady progression of each round. It covers the *for* loop that stops its operation only when the satisfactory condition is met. The status of alive and dead nodes is initialized in **Line 4-Line 5**. The count of alive and dead nodes with respect to the remaining energy of a node is updated in **Line 6-Line 14**. In **Line 9-Line 11**, we compare the count of all dead nodes to the 90% of total nodes. In **Line 15-Line 38**, we present the CH selection, sleep scheduling and steady state phase. In **Line 16**, we check the remaining energy of a node if it is not equal to zero then only it is considered for CH selection and steady state phase. In **Line 17**, we apply TSA [16] optimization method for CH selection. In **Line 18**, the count to CHs is updated. In **Line 19-Line 30**, we introduce the sleep scheduling concept in a cluster. In **Line 20**, we compute the distance between k^{th} and j^{th} node to find if the computed distance is lower than the threshold distance (5 meter). In **Line 22**, we compare the remaining energy of

k^{th} with j^{th} node, and whosoever possesses lower energy than the other, goes to sleep state. In ***Line 31***, the active node in a cluster is assigned TDMA slot for data transmission to CH. In ***Line 33***, CH transmits data to nearest DCS in a single-hop communication. In ***Line 34***, the energy of a node is updated using radio energy model [47]. In ***Line 39-Line 41***, the count to the dead nodes is checked whether it is equal to 90% of total nodes, then the algorithm stops. Finally, in ***Line 43***, the output A is obtained.

D. COMPUTATIONAL COMPLEXITY ANALYSIS

We present the computational complexity of SEOF through the Lemma 1 that we define as follows.

Lemma 1 (:) SEOF terminates in a finite number of iterations i.e., $R_{max} = \mathcal{O}(1)$ and possesses overall computation complexity equals to $\mathcal{O}(R_{max} \times N \times CL \times Total_{Itrn} \times s \times d \times P)$.

Proof (:) SEOF has a fixed count of nodes deployed in the network. Once the steady state phase commences, the nodes gradually starts decreasing their energies. This process occurs till the point when 90% of the total nodes completely exhaust their energies. The energy consumption of each node occurs according to the radio energy model [47]. The whole algorithm is made to run for fixed maximum number of iterations i.e., R_{max} which is commensurate with the 90% dead nodes in the network. Hence, SEOF algorithm terminates with finite iterations.

We discuss the computational complexity of SEOF as follows. The first *for* loop iterates for R_{max} number of rounds and the dead nodes are checked for every value of n. Hence, the complexity of this loop becomes $\mathcal{O}(R_{max} \times N)$. Every n^{th} node is considered for CH selection for every round of R_{max}. Also, **Line 17** computes the CH selection by applying TSA algorithm which takes $\mathcal{O}(Total_{Itrn} \times s \times d \times P)$ time, as determined from Algorithm 1. At the fine grain level, TSA takes $\mathcal{O}(s \times d)$ time to initialize the population, $\mathcal{O}(Total_{Itr} \times s \times d)$ time to compute the fitness of each agent and $\mathcal{O}(P)$ time to model tunicate's behavior. In (**Line 19-Line 30**), the steps for sleep scheduling mechanism are represented. Thus, the commutative complexity of this loop (**Line 15-Line 38**) becomes $O(R_{max} \times N \times CL \times Total_{Itrn} \times s \times d \times P)$.

IV. RESULTS AND DISCUSSIONS

In this section, we firstly discuss the simulation setting employed for the proposed work later, we discuss the performance metrics used in this paper for evaluation of the proposed protocol.

A. SIMULATION SETTING

The simulation of SEOF is done in MATLAB Software version 2016a with the simulation parameters defined in Table 2. The worth-noting point is that the DCS is placed around the network at 10-meter distance from the periphery of each side of the square-shaped network. The purpose of doing so, is to keep the sink out of the network/forest cover. To have a comprehensive simulation investigation, the simulation of SEOF is performed ten times, and the best results are taken with a 95% confidence interval. To examine the SEOF for its

TABLE 2. Simulation parameters.

Parameters	Values
Network size	$100 \times 100 \ meter^2$ (Case I) and $500 \times 500 \ meter^2$ (Case II)
Position of DCS	Cartesian coordinates given as (110,50), (50, 110), (-10, 50), (50, -10)
Total sensor nodes count	100 (Case I) and 200 (Case II)
Normal sensor node's initial energy	0.5
Type of heterogeneous nodes	Normal, Advanced and Super nodes
Number of heterogeneous nodes	Normal=70, Advanced=20 and Super nodes=10 (Case I) and for Case II, Normal=140, Advanced=40 and Super nodes=20
Energy proportions of heterogeneous nodes	Normal: 0.5 Joule, Advanced: 1 Joule and Super nodes: 1.5 Joule
Network's total energy	70 Joules (Case I) and 100 Joules (Case II)
Threshold distance for sleep scheduling	5 meter (Case I) and 10 meter (Case II)
TSA Parameters	**Values**
Search agents	80
Number of generations	1000
Confidence interval	95%

scalability characteristics, we consider two cases of different network dimensions as given in Table 2. First case considers $100 \times 100 \ meter^2$ forest cover area deployed with 100 nodes whereas, second case considers 200 nodes that we deploy in $500 \times 500 \ meter^2$ forest cover area. We empirically evaluate the threshold distance for sleep scheduling and found the optimum values; 5 meter for Case I as depicted from Figure 5 (c), and 10 meter for Case II. The performance evaluation of SEOF is done against the CIRP [35], FLEC [38], GAOC [5], and eeTMFOGA [37].

B. PERFORMANCE METRICS

The efficacy evaluation of SEOF is performed based on the performance measures that are discussed as below.

1) **Stability Period:** It is the count of the rounds before the first node in the network completely exhausts its energy and hence, is said to be dead. We examine SEOF for two cases; for Case I, we find through the simulation analysis that SEOF acquires a stability period of 2747 rounds. However, the other protocols, namely eeTMFOGA, GAOC, FLEC, and CIRP, posses the stability period of 621, 859, 1748, and 2029 rounds, respectively as depicted in Figure 2 (a). The amelioration in the stability period by SEOF accounts for 35.3% and 57.1% vis-a-vis CIRP and FLEC protocols, respectively. For Case II, Figure 2 (b) and Figure 3 (c) illustrate that the stability period of SEOF is having low value due to more number of transmissions in the network.
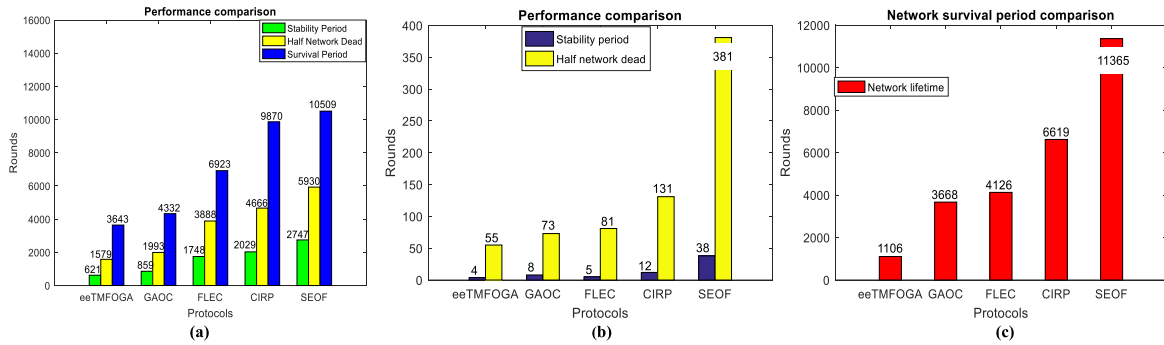
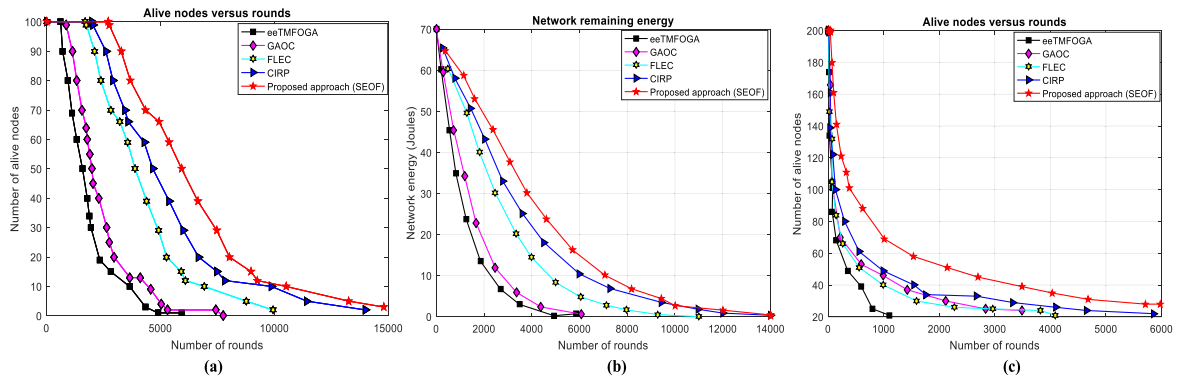**FIGURE 2.** Performance analysis of SEOF for Case I; (a) and Case II; (b, c).

FIGURE 3. Alive nodes versus rounds comparison of SEOF for Case I; (a) and Case II; (c) and network remaining energy comparison of Case I; (b).
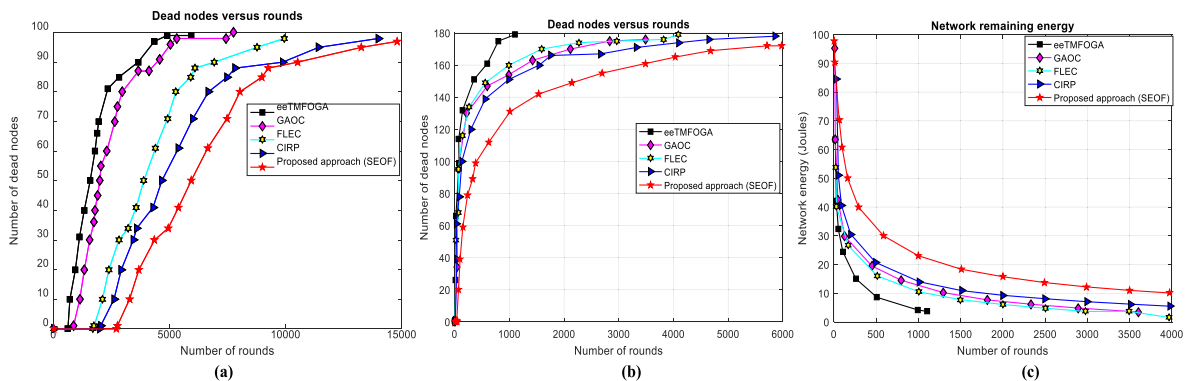

FIGURE 4. Dead nodes versus rounds comparison of SEOF for Case I; (a) and Case II; (b) and network remaining energy comparison of Case II; (c).

The prominent cause behind such improvement in this performance measure is associated with the proposed CH selection and the single-hop communication involved due to the placement of multiple numbers of DCS. Further, the sleep scheduling mechanism helps in energy preservation of all nodes in the network by switching their roles from active to sleep state.

2) **Network survival period:** It is the count of the rounds till 90% of nodes completely exhaust their energies. The reason for not considering 10% is the fact that

they contribute negligibly and do not transmit any vital information. Figure 2 (a), Figure 2 (c), Figure 4 (a) and Figure 4 (b), represent the number of rounds covered until 90% of the nodes are dead. For Case I, Figure 2 (a) elucidates that SEOF covers 10509 rounds, whereas CIRP and FLEC cover 9879 and 6923 rounds, respectively. SEOF accounts for 6% and 51% increase in the network survival period vis-a-vis CIRP and FLEC protocols, respectively. For Case II, Figure 2 (c) shows the network survival period of SEOF is 11365 which is 70% more than that of CIRP.
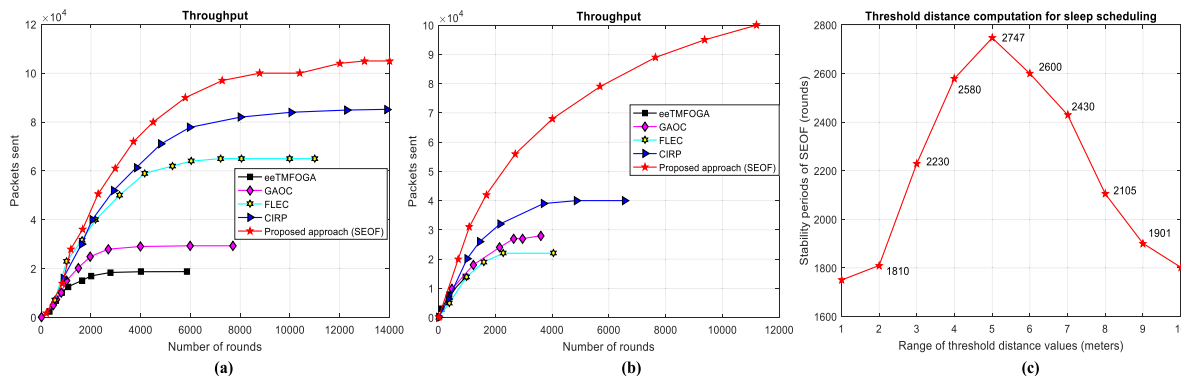
FIGURE 5. Throughput analysis of SEOF for Case I; (a) and Case II; (b) and Threshold distance computation for SEOF (c).

TABLE 3. Percentage amelioration by SEOF against other protocols.

Performance metrics	Name of protocols							
	eeTMFOGA [37]		GAOC [5]		FLEC [38]		CIRP [35]	
	Case I	Case II	Case I	Case II	Case I	Case II	Case I	Case II
Stability Period	342.3	216.6	219.7	660	57.1	375	35.3	850
Half network dead	275.5	592.7	197.5	421.9	52.5	370.3	27	190.8
Network survival period	188.47	927.5	142.5	209.8	51.7	175.4	6	71.7
Throughput	462.3	617.9	269.7	249.9	64.7	344.7	23.8	148.5

The amelioration in this performance metric is due to the energy-efficient election of CH and the decrease in the average distance of the CH nodes from the sink.

3) **Network's remaining energy:** This metric assists in understanding the rate of energy consumption of the nodes while the network is operational. The network's remaining energy corresponding to the total rounds covered is depicted in Figure 3 (b) and 4 (c). The total energy of the network is 70 Joules for Case I and 100 Joules for Case II. Further, it is evident from Figure 3 (b) and Figure 4 (c) that the value of the remaining energy of SEOF is more than the other protocols during its entire run.

The reason behind this improvement is the single-hop data communication among the CHs and the DCS that eventually minimizes the energy consumption.

4) **Throughput:** The count of packets sent to the DCS successfully is referred to as throughput. The throughput analysis of SEOF against the other protocols for Case I and Case II is depicted in Figure 5 (a) and Figure 5 (b), respectively. For Case I, DCS receive 105519 packets in case of SEOF whereas, CIRP, FLEC, GAOC, and eeTMFOGA receive 85209, 64032, 28536 and 18763 packets, respectively. For Case II, the throughput in case of SEOF and CIRP is 100667 and 40500 packets, respectively. However, FLEC, GAOC and eeTMFOGA receive 22633, 28767, and 14021 packets over the rounds.

Due to the enlarged network survival period, the count of packets transmitted or the count of nodes participating in the data transmissions over the particular count of rounds is more than the other protocols.

C. SUMMARY
To summarize our findings, we determine the percentage amelioration by SEOF against the CIRP [35], FLEC [38], GAOC [5], and eeTMFOGA [37] in Table 3. We specify the performance of SEOF for two cases; Case I and Case II considered for investigation for different performance metrics.

V. CONCLUSION AND FUTURE WORK
We propose an intelligent framework namely, SEOF to address the concerns related to the limited energy resources of IoT-based sensor nodes that are deployed in the forest covers for Wildfire Detection (WD). In our proposed framework, we present a novel approach of joint consideration of energy efficient CH selection using a meta-heuristic method named TSA [16] and sleep scheduling methodology to preserve the energy of sensor nodes. We investigate the performance of SEOF through a set of experiments based on four performance metrics namely, stability period, network survival period, network's remaining energy and throughput. During empirical investigation of SEOF, we consider two cases of different network dimensions in terms of count of nodes and network area, to ensure the scalability of SEOF. The simulation results reveal that SEOF delivers superior performance against four state-of-the-art algorithms, namely CIRP [35], FLEC [38], GAOC [5], and eeTMFOGA [37]. More specifically, we find that SEOF ameliorates the stability period by 35.3% and 216% for Case I and Case II,

respectively, vis-'a-vis CIRP [35] and also outperforms the other techniques. The performance improvement of SEOF is acquired at the cost of various assumptions for its real time implementation. However, when the real time implementation of SEOF is performed, there are various factors which may affect the operation of SEOF. The presence of physical obstacles between sensor node, the ability to withstand high temperature when the wildfire is in intact, and many others, can not be ignored ideally.

In extension of this work, the sink placement can be optimized to achieve better network performance. Further, it will be interesting to observe the performance of SEOF under the sink mobility scenario to reduce the cost added in the network with the addition of four DCS.

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