Model for Advanced Sensor Placement in Wildfire Detection Systems

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***Abstract*— Wildfires are a common and dangerous natural phenomenon that harms more than just the natural vegetation. There have been many methods proposed to detect the occurrence of wildfires using randomly placed sensor nodes, yet the optimization of the placement of sensor nodes has not been discussed in studies. This study presents a wireless sensor network (WSN) model supported by an unmanned aerial vehicle (UAV) that focuses on determining optimal locations for sensor placement, optimal determination of cluster heads (CHs), and UAV trajectory to achieve maximum efficiency. The system further introduces the use of time-splitting based simultaneous wireless information and power transfer (SWIPT) to harvest energy for the CHs so as to improve energy efficiency and expand the concept of zero-energy devices within the WSN for wildfire detection.**

***Index Terms*—SWIPT, Wireless sensor network, and Wildfire detection systems**

I. Introduction

WILDFIRES have been a major topic under discussion due to their vast impact, not simply because they harm a massive land-area but also due to their capability to entirely destroy the natural vegetation, wildlife, and living environment within the region they affect. The negative impacts they bring forth are multidimensional and take social, environmental, and economic forms. The European Forest Fire Information System (EFFIS) has recorded wildfires in 45 countries for the year 2022, where the countries faced 16,941 fires that destroyed approximately 1,624,381 hectares (ha) throughout the year [1]. Thus, with advanced technology, various attempts have been made to develop mechanisms for detecting and/or predicting wildfires. Most of these developed methods are based on wireless sensor networks (WSN) [2]–[5]. The location of the sensor nodes plays an important role in determining the accuracy of the sensor network. Sensor nodes are typically battery powered, and these batteries are charged through minute solar panels [6].The number of sensor nodes, location of implementation, network architecture, and charging capacity of the network are some of the key factors that play a crucial role in ensuring the stability of the system.

Most existing WSN based wildfire detection systems are focused on wildfire detection [3], [4], [7]. For example, a method that continuously measures combustible gases, including CO_2, CO, and CH_4, along with temperature and humidity that are required to determine if a forest fire is happening is proposed in [7]. In this method, global positioning system (GPS) location is used to determine the location at which the wildfire occurs. However, this system uses a random sensor placement mechanism without focusing on optimized locations which can result in blind spots being created in high risk zones. A similar approach is adapted in [4] where a flame sensor integrated with LoRA/GPS HAT is used to share the coordinates of fire locations using radio-packet communication. In [3], the authors employ a combination of smoke, temperature, and humidity sensors to detect forest fires. Additionally, they have incorporated a speaker system to guide wildlife away from the fire, demonstrating a practical application.

Use of different technologies for the purpose of detecting fires is the main focus in [8], [9]. A walkie-talkie network is used in [8] to notify people about wildfires that are detected using flame detectors and humidity sensors. A novel approach is implemented in [9] where a sound spectrum analysis is used to determine the wildfire. The sounds made by a spreading fire is used in this system to identify if a wildfire is occurring, however this method shows limited capability of detection until the exact sound spectrum level is reached. An Unmanned Aerial Vehicle (UAV) based forest fire detection system is presented in [10], yet the study has mainly focused on improving the performance of the UAV itself. The accuracy of sensor placement is considered to an appreciable extent in [5] where a zigbee-based system is proposed for the WSN, alongside ordinary network nodes allocated with lower-ability microprocessors randomly deployed in the forest and nearby areas. This network proposes a self-organizing WSN. The system measures parameters such as atmospheric humidity, air temperature, wind speed and direction, and other fire monitoring parameters to determine if a forest fire exists. The system proposed in [11] on the other hand, focuses on the coverage performance of the WSN to sense a time-evolving event, since a forest fire is not dynamic but will evolve with time. This system models the sensor network as a Poisson Point Process, with sensors randomly deployed throughout the forest for early detection.

Almost many existing studies have considered random sensor placement algorithms for the WSN. Though this approach is theoretically accurate, the detection efficiency of the WSN maybe decreased due to the sensors not being located at the key points. Thus, this paper presents a novel sensor placement algorithm that uses the concept of zero-energy devices that can be utilized to implement WSNs for wildfire detection and prediction systems.

The structure of the paper is as follows: Section II introduces the problem description of the study, Section III introduces the concept of zero-energy devices, and Section IV presents the proposed system model. Section V brings the results of the study. Finally, Section VI gives a conclusion with an overview of the future research prospects.

II. Problem Description

In wildfire detection systems, the placement of sensor nodes can be a key determinant of the systems' accuracy and efficiency. It is important to ensure that blind regions are avoided, thus a clear architecture is required that enables the system to achieve the following:

1) Monitor the entire assigned region,
2) Ensure a fast and reliable data transmission process,
3) Ensure coverage on high risk areas.

With these requirements, the introduction of a system that is more reliable and efficient, while being self-sustaining is important. The deliverance mechanism of the sensor network needs to be associated with the ability to ensure that the network is continuously powered while establishing the required power qualities where necessary. The ability to predict the probability of wildfire occurrence is necessary in order to further reduce the damage that can occur. The main objective of this study is to develop a sensor placement algorithm that overcome the limitations in the existing systems.

This study presents a system model that takes into account environmental factors within specific forest environments. It aims to replace random sensor placement algorithms and incorporate an energy harvesting mechanism for use in the sensor nodes, addressing their power requirements. The novelty of the proposed system lies in the fact that no existing studies have established a mechanism to place SWIPT-enabled WSN in a wildfire detection system, considering the fire risk index (FRI) of the region.

III. Zero Energy Devices

Concept of zero energy initially came into discussion with the introduction of zero-energy buildings, which were studied to reduce the energy consumption in buildings [12]. Zero energy devices is a concept that was introduced with the rise of self-sustainable Internet of Things (IoT) models. The main objective of zero energy devices is to ensure that the electronic devices are capable of operating with no external energy requirement. Self-sustaining electronic devices are a major topic of discussion, and concepts related to various energy harvesting mechanisms that can be embedded into the devices are currently being identified while the use of renewable energy has been discussed in many studies.

This concept aligns with the batteryless devices, which are capable of harvesting energy from the external environment without the predominant need of manual charging. This reduces the energy requirement for the devices, improves energy efficiency, and also enables a new dimension in sustainable energy management with its introduction to self-powered smart electronic devices. The introduction of zero-energy Internet of Everything (IoE) devices has been made in [13], where they discuss the implementability of advanced IoE and IoT technologies with no external energy requirements. The adaptation of zero energy devices in WSNs was discussed in [14] with the focus on wireless powered reconfigurable intelligent sources (RIS). Also, sensors that are based on wireless power transfer (WPT) can be considered as zero energy sensors [15]. Within the scope of this project, it is expected to ensure that the concept of zero-energy devices is achieved in the sensor nodes by establishing a self-harvesting mechanism in the sensors. WPT based UAV assisted communication is proposed in [16].

IV. System Model

The system design can be divided into two segments: placing sensors and determining cluster heads (CHs) in appropriate locations within the forest, and gathering and transmitting data to the UAV.

The proposed system model is shown in Fig. 1. This model includes sensor nodes equipped to gather the necessary data for wildfire detection. Additionally, a UAV is introduced to serve as an intermediary between the sensor nodes and the base station. The sensor nodes collect external data and transmit it to the CH, which in turn communicates directly with the UAV. The data transferred to the UAV is cleared from the CH memory, making space for new data until the UAV returns. CHs would be powered using simultaneous wireless information and power transfer (SWIPT) technique, which is a novel addition in the scope of wildfire detection systems, while the other sensor nodes which require more power would be powered by beacons that operate through solar energy.

A. Sensor node placement

Several indices have been proposed in past literature to assess fire risks using both natural and anthropogenic parameters [17]. Fire risk index (FRI) is the product of each corresponding factor multiplied by the weight of risk within the specific the given region as given in Eq. (1), where W_i is the relative weight of a given variable and C_i is the rating for classes within the selected variable.

$$FRI = \Sigma(W_i * C_i). \tag{1}$$

For this study, we consider the FRI to be calculated using Eq. (2) where T is the average temperature factor of the location, H is the humidity factor, WS is the average wind-speed factor, FL is the fuel load or the density of dry vegetation and flammable materials, S is the steepness of the terrain in degrees, A is the direction the slope measured in degrees, and PF is the normalized value of past fire incidents. The values for temperature, humidity and other meteorological values were obtained from previous studies [18], [19]. Past fire incidents factor has been included in order to ensure that the system is capable of prioritizing the necessary locations, that have higher fire probability.

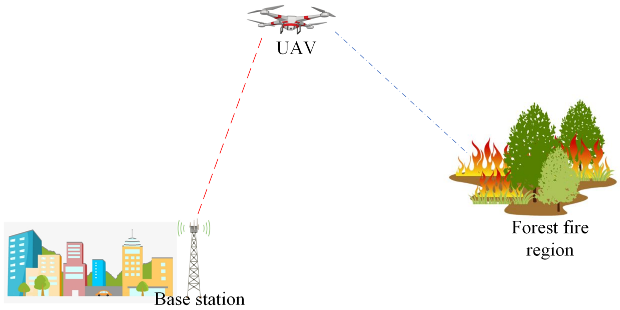

Fig. 1. Communication mechanism in the proposed system model. The data gathered from the sensor nodes are transmitted to the UAV and the UAV communicates with the base station.

Algorithm 1 Optimal Sensor Placement

procedure MAXIMIZE COVERAGE
  Maximize: $\sum(C(i) \cap R)$
  Subject to: $\sum(x_i) \leq n$, $x_i \in \{0, 1\}$
  for each high fire risk point h in H **do**
    if $\sum(C(i) \cap \{h\}) = 0$ **then**
      Place a new sensor at point h, $x_i = 1$
      Update coverage areas $C(i)$,
    end if
  end for
end procedure

In most forests, fires initiate in the same region for each year unless there have been any deforestation events, and this model assumes that no deforestation has occurred. The values w_1, w_2 and w_3 are determined based on the environmental factors of the specific region.

$$FireRisk = w_1 * (0.4 * T + 0.3 * H + 0.3 * WS) + w_2 * (0.6 * FL + 0.2 * S + 0.2 * A) + w_3 * PF. \quad (2)$$

In the system, the forest land area is broken down to small grids and the FRI is calculated for each grid separately. This ensures that the system has proper knowledge on the regions that has higher fire risks and the regions that are to be continuously monitored. The sensor placement is conducted using Algorithm 1. The sensor nodes would be positioned by giving higher priority to the regions that have a higher FRI. In Algorithm 1, S is the set of all possible sensor locations in the grid, $C(i)$ is the coverage area of sensor i, R is the set of high fire risk grid points and n is the number of sensors. H indicates the set of high fire risk points sorted in descending order of fire risk. In the algorithm 1, the prioritization process of sensor node placement is done in a descending order of the FRI to ensure the areas with the highest fire risks are completely covered within the network.

B. Cluster head selection

After determining sensor node positions using FRI values, they are to be grouped into clusters and a CH is to be determined for each cluster. Algorithm 2 is used for sensor

Algorithm 2 Optimized Cluster Modelling

procedure CLUSTERING AND CLUSTER HEAD SELECTION
  Perform clustering based on proximity:
  for each sensor location s_i **do**
    Group s_i with nearest neighbours
    $|c| \leq \alpha$
  end for
  for each cluster c in $clusters$ **do**
    Determine sensor with highest elevation as cluster head: $C\_h(c) = \max\{E(i)\}$
  end for
end procedure

clustering and CH selection. Here, $clusters$ is the set of clusters formed by grouping sensors based on proximity, while $C_h(i)$ is the CH of the cluster to which sensor i belongs, and $E(i)$ is the elevation of each sensor node where sensor i is placed. Clusters are determined based on the proximity of each sensor such that the nearest sensors are grouped together. The CH is expected to be convenient to communicate with the UAV thus, it is selected as the sensor node located at the highest elevation .

C. Data gathering and transmission to the UAV

Each sensor node comprises of temperature, CO_2 and other required sensors and data is transmitted to the CH of each cluster. The CH transmits the data to the UAV which then transmits to the base station.

When attempting to implement systems that supports energy efficiency, SWIPT is considered as an option with greater potential in ensuring performance, mainly at the energy constrained communication links [20]. Time-switching SWIPT protocol is considered in this model, since it has the ability to ensure that the full signal is utilized for energy harvesting during the harvesting period [21]. SWIPT is implemented in the CHs which receives data from the sensors and transmits them to the UAV. As the CH would be switching to data transmission only when the UAV is in the specific sensor region, the CH can allocate time between data gathering and energy harvesting. The proposed algorithm for energy harvesting using SWIPT protocol within the CHs is given in Algorithm 3. It

Algorithm 3 Data Transmission with Time Switching for SWIPT (Cluster Heads only)

procedure SWIPT
  Initialize system and parameters
  for each data transmission cycle **do**
    for each sensor s_i **do**
      Transmit data to $cluster\_h(c)$
      if $cluster\_h(c)$ can harvest **then**
        Perform time switching at $C_{h(c)}$
      else
        Receive data from sensors at $C_{h(c)}$
      end if
    end for
    for each $cluster\_h(c)$ **do**
      Aggregate data from sensors in the cluster
      Store data
      Transmit data to UAV
    end for
  end for
end procedure

Algorithm 4 UAV Trajectory Planning for Cluster Head Coverage

procedure UAV
  Initialize UAV, base, CHs, and parameters
  Initialize **Run_Counter**: $R \leftarrow 0$
  Initialize **UAV_Position**: $u \leftarrow$ base
  while not termination condition met **do**
    $R \leftarrow R + 1$
    if $R \mod \alpha = 1$ **then**
      Update trajectory for maximum coverage: **path** ← MaxCoveragePath()
    end if
    Find closest unreached CH to **UAV_Position**: $c \leftarrow$ closest(**UAV_Position**)
    Move UAV from **UAV_Position** to c
    UAV_Position $\leftarrow c$
    Update reached CHs: $reachedCHs \leftarrow reachedCHs \cup \{c\}$
    if $R \mod \alpha = 0$ **then**
      Clear $reachedCHs$ and reset **path** for next runs
    end if
    Process data from c
  end while
end procedure

facilitates efficient data collection and power management in a SWIPT scenario by coordinating data transfer from sensors to CHs, optimizing energy usage at CHs, and relaying the data to the UAV. The dynamic allocation of time for data transmission and power harvesting between the signals received from sensor S_i to the CH $C_h(c)$ enables the optimization of energy harvested.

D. UAV Trajectory

The UAV needs to reach the CHs in order to collect the stored data and transmit to the base station. It cannot reach all the CHs in a single cycle, therefore a sophisticated trajectory planning that would reach all the CHs during a series of cycles is required. Determination of UAV trajectory should maximize coverage, reach all CHs periodically, and have a rotation in the CHs reached. Algorithm 4 assumes that the UAVs' position is represented by waypoints, and it selects the closest path to maximize CH coverage. The UAV starts from a designated base location and iterates through flying cycles. In each flying cycle, it moves to the closest unreached CH to maximize coverage.

At each α[1] run, the trajectory is updated for optimal coverage, and reached CHs are reset. This guarantees that the entire forest is covered and all CHs are reached by the UAV within specific time intervals. Algorithm 4 ensures effective data collection in the sensor network while maintaining a trade-off between coverage and flying duration through trajectory planning. With the allocated time gap between data gathering from a single CH, the CH itself receives the advantage of having sufficient time to gather data from all its sensor nodes while also harvesting energy such that it has enough energy to transmit the data towards the UAV.

[1]The value of α is selected depending on the number of cluster heads, and this can vary depending on environmental and other conditions.

V. Results and Analysis

A. Results

This study aimed to provide an optimal sensor placement mechanism to replace the current random sensor placement methods. This approach aims to reduce errors associated with the WSN by ensuring coverage of prominent regions with high risks. The system was tested through an approximate simulation using a 5 km square block of forest. The weights of each parameter were equally distributed, and environmental parameters were gathered based on general data to calculate the Fire Risk Index (FRI) values. The elevation of the land was obtained from geological data available online.

Fig. 2 indicates the grid points with the FRI values shown using a color code, where red color indicate regions with the highest fire risk, and blue color indicates those with the lowest fire risks. As depicted in Figure 2, sensor placement has been achieved by prioritizing FRI, ensuring optimal coverage of regions with higher fire risks. For simulation purposes, the number of sensor nodes within the system was limited to 30, each with a coverage radius of 0.3 km. Therefore, the system considered regions with the highest risks as suitable locations for sensor node positioning.

With the obtained sensor locations, clustering was conducted to identify clusters and CHs. This process utilized the provided Algorithm 2, employing k-means clustering for clustering, and CH selection prioritized elevation data. The results are depicted in Fig. 3. The clusters are formed based on sensor nodes in close proximity, facilitating efficient communication with the CHs.

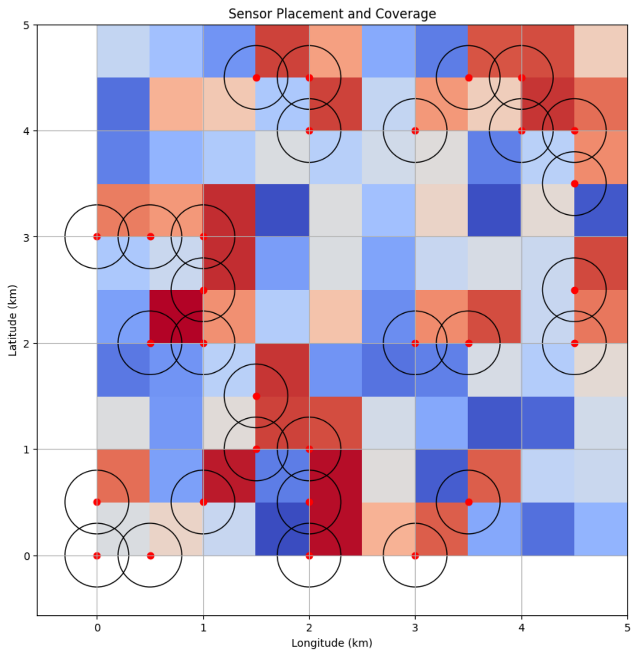

Fig. 2. Sensor placement in the land area based on FRI. Red zones indicate the regions with the highest risk and the blue zones indicate those with the lowest fire risk.

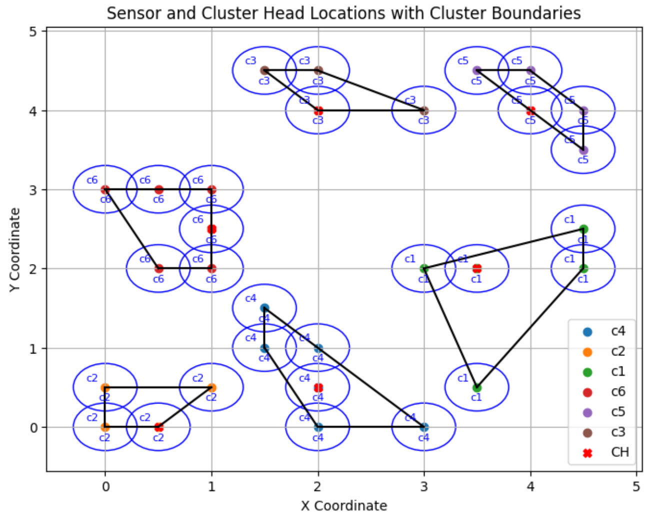

Fig. 3. Clustering and CH selection based on the sensor placement obtained in Fig.2. The clusters are based on the proximity and the CHs are selected based on the elevation of the sensor node.

Fig. 4 showcases the trajectory outline of the CH placement. Since there are 6 clusters generated in the model, α = 5 is considered. The selection of this value as 5 for UAV trajectory planning based on a reasoned choice aimed at achieving a balance between data acquisition frequency and operational efficiency. Further, it is assumed that the base station is near the point (0,0), therefore each trajectory starts and ends near this point.

With the proposed trajectory outline in Fig. 4 the opportunity to expand the use of time-splitting SWIPT model in the CHs arises. The trajectory planning provides reasonable time allocation for the CH to communicate with the UAV and for the sensors acting as moderators

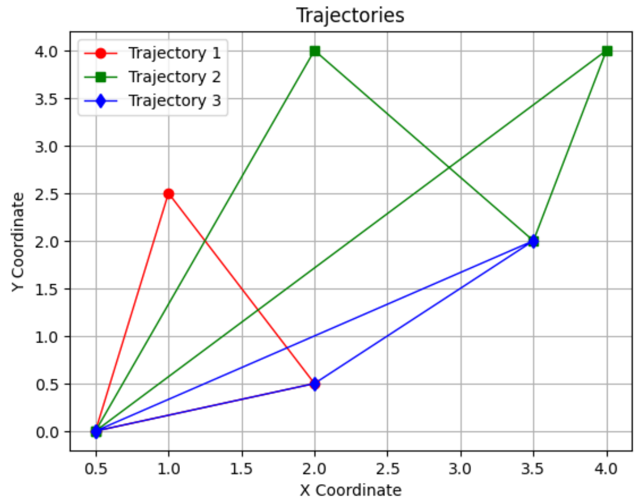

Fig. 4. UAV trajectory for the identified CHs. There are three trajectories and each fall to cover two CHs at a given time allowing the remaining CHs to perform SWIPT during the free time gap.

to communicate with the neighbor sensor and CH for data transmission. The accuracy of fire detection is enhanced through the UAV trajectory since it ensures that the entire region is covered within a given time period.

B. Efficiency comparison

To compare the efficiency of the proposed algorithm with existing algorithms, the same system was implemented with random sensor placement as shown in Fig. 5. Then, we compared the efficiency of sensor placement of the proposed algorithm with the random placement algorithm using Equation (3).To make the efficiency comparison more accurate, we considered the distance between sensor placements. If two sensors were located within 0.2km [2] of each other, we eliminated the second sensor node. The distance $d_{i,j}$ between sensors was calculated as $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$, where x_i, y_i and x_j, y_j are two sensors.

$$\text{Efficiency} = \frac{\text{Covered High-Risk Cells}}{\text{Total High-Risk Cells}} \tag{3}$$

With efficiency calculation, it is seen that coverage efficiency of the high fire risk regions in the proposed algorithm was 0.68, while that of the random sensor placement algorithm was 0.59. Therefore, is evident that the proposed algorithm has a higher efficiency of FRI coverage which enables better detection capability.

When comparing Fig.2 and Fig.5, the proposed algorithm ensures that all the high risk points are covered while the random sensor node placement algorithm requires more nodes to assume full coverage. The random sensor node positioning algorithm does not work effectively with the presented number of sensor nodes. Since random sensor placement methodology has no knowledge on the exact required number of sensors, the implementation cost

[2]Since the coverage radius of each individual sensor is 0.3km, any two sensors located less than 0.2km apart senses the same region.

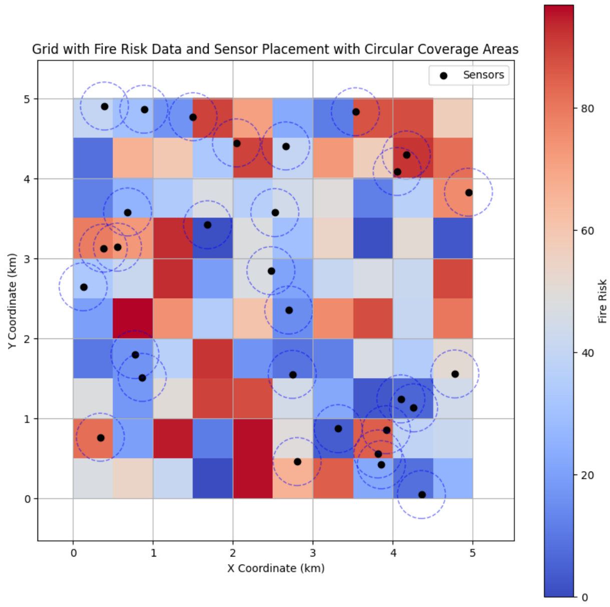

Fig. 5. Implementation using random sensor placement algorithm without the use of FRI data. As can be seen, several high fire risk zones are ignored when positioning sensors, thereby reducing efficiency.

is considerably high. But with the proposed model, the knowledge of accurate positioning of sensor nodes to obtain higher accuracy in the detection process reduces the overall nodes required. It also enables the system to be capable of reaching a massive coverage area, thereby creating an

VI. Conclusion

In conclusion, it is seen that this model provides an accurate placement of sensor nodes within a wildfire detection system while enabling an advanced energy harvesting approach to increase system sustainability. It also establishes an opportunity to address the energy requirements of sensor nodes by stepping away from the traditional solar powered battery units and allowing to utilize SWIPT as an energy harvesting mechanism within forest fire detection systems. Further research may be carried related to adapting SWIPT in further positions within the WSN to achieve more energy efficiency, and to enhance the communication link between the sensor nodes.

Acknowledgment

This work was supported, in part, by the national funds through FCT - Fundação para a Ciência e a Tecnologia via AIEE-UAV(no. 2022.03897.PTDC) and COPELABS (no. UIDB / 04111/2020), by the European Commission via Marie Skłodowska-Curie Actions (MSCA) as part of the project REMARKABLE (No. 101086387) and by the COFAC via the project AOEE-WiPS (COFAC/ILIND/COPELABS/2/2022).

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