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A Coverage and Obstacle-aware Clustering Protocol for Wireless Sensor Networks in 3D Terrain

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Abstract

In Wireless Sensor Networks (WSNs), clustering techniques are often used to optimize energy consumption and increase Packet Delivery Rate (PDR). To date, most of the proposed clustering protocols assume that there is a Line of Sight (LOS) between all the sensors. In fact, most of the available WSN simulators assume the use of optimistic path loss models that neglect the effect of obstacles on the PDR. However, in real situations such as in 3D terrains, obstacles can interfere this LOS. Moreover, while clustering, it is also important to maintain the coverage of a given Region of Interest (ROI). Therefore, finding an integrated solution for both clustering and coverage problems in an irregular 3D field becomes a pressing concern.

In this paper, we first adopt an obstacle-aware path loss model to reflect the effect of obstacles on the communication between any pair of sensors. To that end, the Castalia simulator is adapted to use this proposed path loss model. Then, we introduce a Coverage and Obstacle-Aware Cluster Head Selection (COACHS) protocol to solve the cluster heads selection problem while maintaining a good coverage of a WSN deployed in an irregular 3D field. Sim-

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ulation results demonstrate that the effect of obstacles on the PDR cannot be neglected. Moreover, comparative evaluation results show that COACHS outperforms other competent protocols in terms of PDR while simultaneously maintaining an acceptable energy consumption and a good coverage of the ROI.

Keywords: WSNs, Cluster Head Selection, ROI Coverage, Obstacles, 3D rolling terrain, Energy Consumption

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1. Introduction

Multiple clustering protocols have been proposed in the literature to optimize the energy consumption in Wireless Sensor Networks (WSNs). The main objective of a clustering protocol is to find a subset of sensor nodes that can act as Cluster Heads (CHs). Finding the optimal set of CHs has been proven to be a Non-deterministic Polynomial (NP)-hard optimization problem that has many conflicting objectives [1]. Most of these protocols assume that the sensors are deployed in a Two-Dimensional (2D) network field. However, there is an increasing number of WSNs applications in which the network field is a Three-Dimensional (3D) rolling terrain, such as volcano monitoring and landslide detection. Although recent studies have proposed clustering protocols for 3D WSNs [2, 3, 4], these studies assume that the field is a 3D volume where sensors can be positioned freely within the whole 3D space. Compared to this free deployment, deploying sensors on rolling fields is different as sensors can only be deployed on the exposed surface, not freely within the 3D space. Furthermore, clustering protocols developed for 2D fields cannot be applied directly in such applications because the nature of 3D rolling fields may lead to the creation of obstacles in the network field. These obstacles have a substantial impact on the link quality between the communicating sensors as they cause an increased path loss. Therefore, determining the optimal set of CHs on a

3D rolling field is a critical task. Data delivery reliability is considered a key requirement in WSNs [5, 6]. In order to realize this requirement, clustering protocols should ensure high-quality links between the cluster members and their associated cluster heads. The Received Signal Strength Indicator (RSSI) is considered a prominent metric to assess the link quality between the transmitter and the receiver sensors. The RSSI calculation depends mainly on the adopted path loss model. Therefore, the performance of clustering protocols critically depends on the ability to accurately model the path loss of the communication signal between the transmitter and the receiver. A common limitation in most of the previously proposed clustering protocols is the assumption of the free space path loss model. The fundamental assumption behind this model is that the transmitter and the receiver sensors have a Line of Sight (LOS) communication with no obstacles of any kind [7]. In real situations, there are almost always obstacles in the path between the transmitter and the receiver. Therefore, the free space path loss model is considered ideal and optimistic for predicting the path loss between any two sensors since it does not take the obstacles effect between the transmitter and the receiver into account [8]. Most of the available WSNs simulators assume the use of the free space path loss model [9, 7]. The log-normal shadow fading model is proposed as an attempt to construct a more realistic path loss model by simulating the path loss around the sensors. Yet, this model does not account for the effect of the obstacles on the communication signal. Another significant limitation is that most of the existing clustering protocols assume the use of the first order radio model [10, 11]. However, this energy model is idealized and fundamentally flawed for modelling radio power consumption in sensor networks [10, 11, 12].

Castalia is a popular and very efficient WSN simulator that provides a well-designed channel model [9] and adopts a realistic energy consumption model based on the characteristics of the Chipcon CC2420 radio transceiver data sheet. However, Castalia adopts the log-normal shadow fading model and hence shares the same drawback as most of the available WSN simulators with regard to accurately modelling the path loss in case of No Line of Sight (NLOS) communication, i.e. when there are obstacles between the transmitter and the receiver.

1.1. Contributions

In this paper, we design, implement and evaluate a coverage-aware CHs selection protocol (called COACHS) for WSNs in the presence of obstacles in 3D rolling fields. Since the CHs selection problem has been proven to be a Non-deterministic Polynomial (NP)-hard problem with many conflicting objectives, a Pareto-based Evolutionary Algorithm (EA) is adopted to solve this problem. The proposed protocol takes into consideration the following key requirements: coverage ratio, energy efficiency, data delivery reliability, and protocol's scalability. To evaluate the performance of the proposed protocol, we compare the simulation results against well-known clustering protocols, in the existence of obstacles and under a realistic energy consumption model. More precisely, the main contributions of this paper are listed below.

- We adapt an obstacle-aware path loss model to evaluate the effect of obstacles in the communication between any two sensor nodes. To achieve that, we implement a visibility function to find obstacles on the path between any two sensors. This function is implemented based on the Bresenham's algorithm. Based on the adopted path loss model, a path loss map is derived. The Castalia simulator is then modified to use this map to calculate the path loss and the RSSI values between any two sensors in the network.
- We propose a new EA-based coverage-aware clustering protocol for 3D WSNs where the network field is a 3D rolling terrain.

- To realize the aforementioned contributions, the network field is modelled using the Digital Elevation Model (DEM) to account for different elevations, and hence obstacles, in the field.

To the best of our knowledge, the proposed clustering protocol is the first to consider and test the obstacles' effect on the communication between the sensors as well as to maximize the coverage of the ROI. Moreover, experimental validations are performed on real elevation data for 3D terrains.

1.2. Paper Organization

The remainder of this paper is organized as follows. Section 2 presents the related work on protocols designed for 3D WSNs. Section 3 presents the system model and assumptions. The design of the proposed protocol (COACHS) and the problem formulation are provided in section 4. A detailed analysis of the simulation results is provided in Section 5. Finally, Section 6 concludes the paper and highlights future research directions.

2. Related Works

The Low Energy Adaptive Clustering Hierarchy for 3D WSNs (LEACH-3D) protocol [13] is a direct extension of the original LEACH protocol and is considered the first clustering protocol designed for 3D WSNs. The first order radio model, which is initially proposed by LEACH, is extended to work for 3D WSNs. Based on this extension, the authors prove that the effect of the 3D environment on clustering protocols cannot be neglected. LEACH-3D uses a variable number of CHs and different number of CHs could be elected each round.

A Fuzzy-based Clustering Scheme for 3D WSNs (FCM-3) is proposed in [2] to apply clustering protocols in 3D WSNs. The proposed protocol assumes the radio model which is proposed in [13]. The adopted fuzzy approach optimizes one objective function which is defined as minimizing the total energy consumption and is constructed by combining the distances between sensor nodes and their corresponding CHs and between the CHs and the Base Station (BS) into the radio model. FCM-3 defines two constraints to ensures single-hop connections for the intra-cluster and inter-cluster communication. Similar to LEACH-3D, the number of CHs is variable. However, experimental results show that FCM-3 achieves the best performance when the number of CHs is from 20% to 30% of the network size, which is considered a high number.

A Particle Swarm Optimization (PSO)-based Protocol for CHs selection (PSO-CH) [14] is a centralized PSO-based protocol that is used to find the optimal set of CHs. The PSO-CH protocol considers the following properties: the network's energy efficiency, data transmission reliability, and the protocol's scalability. The objective function that is used to evaluate each candidate solution is defined as the weighted sum of three sub-objectives, each of which is related to the aforementioned properties. PSO-CH is designed and implemented under realistic networks settings and realistic energy consumption model. The link quality estimation in PSO-CH is based on the Received Signal Strength Indicator (RSSI) of received packets.

All the aforementioned protocols are applicable to 3D WSNs. However, the path loss model adapted by these protocols ignore the effect of the obstacles on the communication between the sensors. They also assume that the field is a 3D volume where the sensors can be positioned freely within the field. Moreover, all these protocols assume the use of an ideal energy consumption model.

The research work in [15] investigates the impact of various path loss models on the performance of the Ad Hoc On-demand Distance Vector (AODV) routing protocol. In this work, the effect of varying the number of obstacles on the Packet Delivery Rate (PDR) is analyzed for the different path loss models under comparison. In order to achieve that, the Network Simulator-2 (NS-2) is enhanced to accommodate the different path loss models. Simulation results indicate that the performance of the AODV protocol, in terms of the PDR and the mean delay, is affected by the increase in the number of obstacles. Although no specific path loss model is recommended, the authors established that using simple path loss models is considered very optimistic in estimating the performance of routing protocols.

The Surface-Level Irregular Terrain (SLIT) path loss model [16] is a semi-empirical path loss model for WSN with irregular terrain. The SLIT model uses the terrain information, expressed by the DEM data, to provide a fast and an accurate estimation of the large-scale path loss due to the obstacles existing in the field. The total path loss is expressed as a function of both the free-space path loss and the path loss due to the obstacles in the field, which is calculated using the Epstein-Peterson diffraction loss model [17]. In order to verify the SLIT model, empirical experiments are conducted and the average difference between the measured results and the predicted results from the SLIT model are recorded. Experimental results have shown that the SLIT model provides an accurate path loss model that accounts for the terrain profile.

In this paper, we adopt the SLIT path loss model [16] and propose an obstacle-aware clustering protocol for 3D WSNs to evaluate the effect of obstacles on clustering protocols.

3. The System Model

The 3D rolling field is modelled using the Digital Elevation Model (DEM). The DEM is a digital representation of a given ground surface topography or terrain. In the DEM, the network field is represented as a matrix of cells, where each cell holds a value that represents the average elevation of the area contained by that cell. DEMs are commonly built using remote sensing technology or from land surveying, and are usually available to download. For example, the geospatial data extraction tool [18] is part of Natural Resources Canada's altimetry system designed to meet the users' needs for elevation data and products. This tool provides data from seamless national datasets based on custom-defined geographic area and customized data options. The main motivation to adopt the DEM in our proposed protocol is to be able to simulate a realistic 3D rolling field and to find the obstacles between any two sensor nodes in the network. The sensors are assumed to be uniformly deployed in a 3D rolling field. Based on the DEM data, the height coordinate of a sensor located at position (x, y) is restricted to the field's elevation at that specific position.

For the energy consumption model, a discrete-based realistic model which is based on the characteristics of the Chipcon CC2420 radio transceiver data sheet [19] is used. The total energy consumed by sensor node n, $consumedE_n$, is calculated as follows [20]:

$$consumedE_n = \sum_{statej} P_{statej} \times t_{statej} + \sum_{tr} E_{transitions} \tag{1}$$

The index $statej$ refers to the energy states of the sensor: sleep, reception, or transmission. P_{statej} is the power consumed in each $statej$, t_{statej} is the time spent in the corresponding state, and tr is the number of transitions for S. The energy spent in transitions between states, $E_{transitions}$, is also added to the node's total energy consumption. The different values of P_{statej} and $E_{transitions}$ can be found in [19].

For the path loss model, we adopt the SLIT path loss model [16] to find the path loss between any two sensors.

For the coverage ratio computation, the target terrain surface is first partitioned using Triangular Irregular Network (TIN) [21]. Fig. 1 depicts the surface triangularization on the xOy-projection plane [1]. Then, a revised 3D binary sensing model [22] is applied to measure the coverage redundancy, which is a network coverage performance indicator.

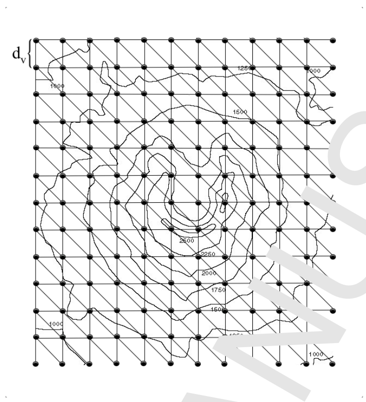

Figure 1: Triangular Irregular Network on the xOy-Projection Plane of the Target Terrain

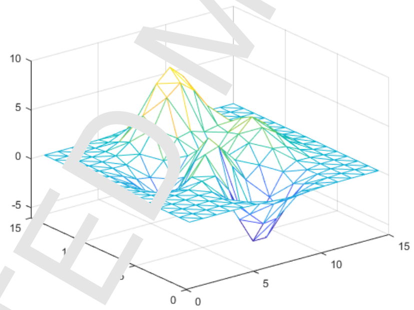

Figure 2: Trimesh of Rolling Terrain Partition (Triangular Irregular Network)

[1]Let xOy be a reference plane. Any point T(x_t,y_t,z_t) in a 3D space can be projected onto this xOy plane, and the projection point $T'(x_t,y_t)$ is referred to as the xOy-projection of T.

4. A Coverage and Obstacle-aware Clustering Protocol for WSNs with Rolling Field

The network operating time of the proposed protocol is divided into rounds. Each round consists of two phases, the set-up phase, and the steady-state phase. The operation of these phases is similar to that of [14]. In this paper, we focus on the protocol adopted by the BS in the set-up phase to find the optimal set of CHs and clusters. The proposed protocol includes six different processes as illustrated below:

4.1. DEM Extraction

The geospatial data extraction tool [18] provided by Natural Resources Canada is used to extract the elevation data for a given network field. Based on the DEM data for a given network field, the BS constructs an elevation matrix that holds the elevation data for all the cells contained by the network field. The ArcGIS software package is utilized to generate and extract the elevation data given the DEM data for that field.

4.2. LOS Algorithm

A Line of Sight (LOS) algorithm is needed to find the obstacles in the communication link between any two sensors in the field. In this paper, the Bresenham LOS algorithm is utilized to implement the visibility function. The Bresenham algorithm is often used in computer graphics for line drawing on 2D surfaces. In this paper, we have modified it to be used for LOS determination on 3D rolling fields. In this algorithm, if the elevation of any corresponding points between the transmitter and the receiver does not cut the virtual line drawn between them, then there is a LOS between the transmitter and the receiver. Otherwise, it is said that there is NLOS (non-LOS) between them. In this paper, an obstacle is defined as the point which has an elevation higher than that of the transmitter or the receiver. The LOS algorithm returns a visibility matrix that has N rows and N columns, where N is the total number of sensors. This visibility matrix holds the path loss of all the obstacles between any two sensors in the network.

4.3. Path Loss Map Calculation

Based on the visibility matrix, a path loss map is generated by the BS. This map reflects that path loss between any two communicating sensors in the network and is calculated using the SLIT path loss model. The Castalia simulator is then modified to use this path loss map instead of the one provided by the log-normal shadow fading model to calculate the propagation loss and the RSSI values for the links between any two communicating sensors.

4.4. TIN Surface Partition

A Triangular Irregular Network (TIN) partition is applied to the target network field. First, we generate a $m*n$ grid on a xOy-projection plane of the target terrain (see Fig. 1). Let d_v denote the distance between any pair of neighbouring vertices on a grid line. The elevation value of each vertex is obtained from the DEM data utilizing a linear interpolation method [23]. As shown in the figure, a given vertex $v_{i,j}(1 \leq i \leq m, 1 \leq j \leq n)$ has a one-to-one mapping to the given terrain surface. We generate a triangular network that contains $2(m-1)(n-1)$ triangles using these vertices. We calculate the expected coverage ratio of the ROI utilizing this triangular network.

4.5. Redundant Coverage Calculation

Before deriving the redundant coverage value for each sensor, we use a Breadth First Search (BFS) like approach [24] to pinpoint a set of triangles that are covered by a specific sensor. Since a fine-grained partition is required to model a complex rough terrain surface and because the target terrain can be much larger than the scale of each triangle, a brute force approach is unattainable.

In this paper, we use a binary 3D sensing model [22]. In this model, if a point p in the network field is located within the sensing range r of sensor node n, then it is assumed that p is covered by n. The sensing region of n is modelled as a sphere centred at n with a sensing radius r. We say that a triangle in the ROI is covered by sensor n if its three vertices are covered by n, and uncovered otherwise.

We also use a redundant coverage formula as proposed in [25]. In this formula, the redundant coverage D_i is defined as:

$$D_i = \frac{S_i}{S_{i1} + \frac{S_{i2}}{2} + \frac{S_{i3}}{3} + ... + \frac{S_{iN}}{N}} \tag{2}$$

where S is the entire coverage of each sensor. For each sensor i, let S_i be the sensor's coverage area, S_{i1} is S_i minus the area that overlaps with other sensors. S_{i2} is the overlapping area between two sensors' covering area, and S_{iN} is a N-covering area that is the overlapping area by N sensors. Therefore, S_i can be represented as:

$$S_i = S_{i1} + S_{i2} + S_{i3} + ... + S_{iN} \tag{3}$$

Intuitively, the more redundant a node is, the more it should be selected as a CH, so that even if a number of redundant nodes run out of battery, the network redundancy is not effected.

4.6. Finding the Optimal Set of CHs

Once the modified RSSI values are calculated, the BS runs an EA-based algorithm to find the optimal set of CHs. In this paper, we adopt the Non-dominated Sorting Genetic Algorithm II (NSGA-II) as an optimization tool to find the optimal set of CHs. The problem formulation for the adopted NSGA-based algorithm is provided in the next section. Table 1 presents the notations used in this paper.

Table 1: Notations

Symbol	Definition
P	Population generated from the adopted EA
N	Total number of sensors
n	Sensor number n, $0 \leq n < N$
C_i	Individual number i of P
$X_{i,n}$	Component number n of C_i
K_i	Total number of clusters generated from C_i
CL_{k_i}	Cluster number k generated from C_i, $0 \leq k_i < K_i$
CH_{k_i}	Cluster head number k generated from C_i, $0 \leq k_i < K_i$
$\|CL_{k_i}\|$	Number of sensors clustered in CL_{k_i}
$E(n)$	Remaining energy of node n
$initialE(n)$	Initial energy of node n
$RSSI_{(n,CH_{k_i})}$	RSSI value for the link from n to CH_{k_i}
$LQ_{(n,CH_{k_i})}$	Link quality for the link from n to CH_{k_i} $LQ_{(n,CH_{k_i})} = \frac{RSSI(n,CH_{k_i})}{-100}$
$D_{i,n}$	Redundant coverage for the sensor node n from C_i $D_{i,n} = \frac{S_{i,n}}{\sum_j^N (S_{nj}/j)}$

4.6.1 Decision Variables

In the proposed protocol, a sensor node may be in one of two states: a CH, or non-CH. To find the optimal set of CHs, a random initial population P is generated and evolved by the adopted EA. Each candidate solution (Chromosome) C_i in P has a dimension equal to the network size minus the BS (i.e., $N-1$). Binary encoding is adopted to represent each chromosome, where the size of each component of C_i is 1 bit.

Let, $C_i = [X_{i,1}, X_{i,2}, X_{i,3}, ..., X_{i,N-1}]$ be the i_{th} chromosome of P where each component, $X_{i,n}, 1 \leq n \leq N-1$ maps the state of sensor n. Each component $X_{i,n}$ of chromosome C_i is initialized with either 1 to indicate that sensor n is a CH node, or 0 to indicate that sensor n is not a CH. It should be noted that this encoding process will result in a variable number of CHs. Table 2 shows the random sequences created for two individuals in P on a network including 10 sensor nodes other than the BS. Each row presents a solution for a chromosome in P. For example, in chromosome C_1, sensors 2, 5 and 10 are CHs while the rest of the sensors are non-CH nodes.

Table 2: Chromosome Population

Node ID	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
C_1	0	1	0	0	1	0	0	0	0	1
C_2	0	0	1	1	1	0	0	0	1	0

The clusters are formed by associating each non-CH node to its closest CH that has the lowest RSSI value. Once the clustering process ends, each sensor node belongs to only one cluster and each cluster head node acts as the CH of exactly one cluster.

4.6.2. Objective Functions

Each chromosome C_i is evaluated according to four objective functions, which are briefly described in Table 3 and defined below.

Table 3: Objective Functions

Objective Function	Description	Goal
K_i	Minimize the total number of CHs	Save energy
U_i	Minimize the number of unclustered sensors	Enhance scalability
L_i	Maximize the link quality between clusters	Data delivery reliability
E_i	Maximize the total remaining energy of the CHs	Balance energy consumption
R_i	Maximize the redundant network coverage of CHs	Optimize network coverage

$$K_i = \sum_{n=1}^{N-1} 1, \quad \text{if } X_{i,n} = 1 \tag{4}$$

$$U_i = N - \sum_{k_i=1}^{K_i} |CL_{k_i}| \tag{5}$$

$$L_i = \max_{k=1,2,\ldots,K} \frac{\sum_{n \in CL_{k_i}} LQ_{(n,CH_{k_i})}}{|CL_{k_i}|} \tag{6}$$

$$E_i = \sum_{n=1}^{N} \frac{initialE(n)}{E(n)}, \quad \text{if } X_{i,n} \neq 00 \tag{7}$$

$$R_i = \frac{1}{K_i} \sum^{K_i} D_{i,k_i} \tag{8}$$

It should be noted that the calculation for L_i in the proposed protocol depends on the newly derived RSSI values which in turn depend on the generated path loss map. The pseudo-code of COACHS executes in an arbitrary node n is shown in Algorithm 1. The proposed protocol utilizes a timer-event model to represent each step executed in a WSN node. The setTimer function has two parameters: *Event_Name* and *Time*. *Event_Name* is an index for all steps, and *Time* is a double-typed value representing time elapsed. At the beginning of each round, each node first searches their neighbours (FIND-NBRS) by broadcasting their own ID then waiting for the responses from their neighbours. Then, each node broadcasts their ID, residual energy, neighbours' IDs and their respective RSSI to the BS. Once received this information, the BS starts a series of processes to find the optimal CHs. In detail, the DEM data for a given network field is first extracted as described in Section 4.1. Then, a line of sight algorithm, the Bresenham's algorithm to be precise, is utilized to compute the visibility matrix. Based on this visibility matrix, a path loss map which reflects the path loss between any pair of communicating sensors is generated. This path loss map, containing the propagation loss and the RSSI values for the links in the network, is later used as an input for the NSGAII optimization. The network coverage information for each single node is also required for the NSGAII optimization. In order to obtain this, A TIN partition is applied to the target field. Then, Equation 3 is applied to compute the redundant network coverage. Ideally, the more redundant a node is, the more it should be selected as a CH, so that network coverage is not largely affected even if a redundant node runs out of battery. At this point, the BS launches the NSGAII optimization, using the path loss map, redundant coverage and remaining energy level of each sensor as inputs. At last, the BS configures the set of optimal CHs then reset the status of each sensor. As a result, the CHs and CMs enter a steady-phase. Each CHs establishes communication channels, aggregates packets and relays packets to the next hops. Each CMs relays packets to its CH, then goes to sleep-mode. COACHS then proceeds to the next round.

5. Simulation Results and Analysis

The COACHS protocol and the proposed path loss model are implemented in Castalia. In addition, we have implemented both LEACH-3D and PSO-CH. The simulations are performed on elevation data from the Armadillo Peak volcano in British Columbia, as illustrated in Figure 3. The DEM of this field is obtained using the geospatial data extraction tool [18] provided by Natural Resources

Algorithm 1: Pseudo-code of the proposed protocol

```
begin Procedure startup()
    setTimer(START − ROUND, 0.0);
end
begin Procedure timerFiredCalback(index)
    switch index do
        case START − ROUND : do
            double timer = uniform(0.0 , r);
            setTimer(FIND − NBRS, timer);
            setTimer(BROADCAST − INFO, r);
            if isBS then
                setTimer(FIND − CHs, n);
            end
            else
                setTimer(RUN − STEADY − PHASE, m);
            end
            roundNumber + +;
            setTimer(START − ROUND, roundLength);      ▷ r, n, and m are random times
        end
        case FIND − NBRS : do
            broadcast (ID);
        end
        case BROADCAST − INFO : do
            broadcast (ID, residualEnergy, neighbours′ IDs and their RSSI);
        end
        case FIND − CHs : do
            dem_Matrix = extractDEM();
            visibility_Matrix = runLOSAlgorithm(dem);
            calculatePathLossMap(visibility_Matrix);
            partitionTINSurface();
            calculateRedunduntCoverage();
            optimalCHs = runNSGAII(NetworkInfo);      ▷ find optimal CHs
            broadcast(configuration = optimalCHs + sensorsstates);
        end
        case RUN − STEADY − PHASE : do
            if (!isCH||!isCM) then
                setStateSleep();
            end
            if (isCH) then
                clusterLength = clusterMembers.size();
                setTimer(START − SLOT, clusterLength × slotLength);
            end
            else
                setTimer(START − SLOT, myTDMATurn × slotLength);
            end
        end
        case START − SLOT : do
            setTimer(START − SLOT, clusterLength × slotLength);
            if (isCH) then
                aggregatePackets();      ▷ aggregate packets
                processBufferedPackets();      ▷ send packets to next hop
            end
            else
                processBufferedPackets();      ▷ send packets to CH
                setTimer(END − SLOT, slotLength);      ▷ go to sleep mode at end of slot
            end
        end
        case END − SLOT : do
            if (!isCH||!isCM||!isRelayNode) then
                setStateSleep();
            end
        end
    end
end
```

Canada. To generate the elevation data, a 20×20 fishnet is constructed using the ArcGIS software on a scaled version of the network field. The network field is scaled down to 100×100 meters. The sensors are deployed randomly and their position is restricted by the elevation of the rolling field. The initial energy of the sensors is set to 18720 J. Each round is 500s and the number of rounds is set to 5. We vary the total number of sensors from 100 to 500.

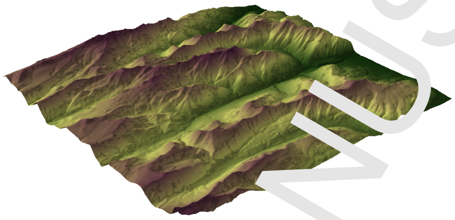

Figure 3: Scaled Version of the Armadillo Peak Volcano in British Columbia

In this section, we consider the following objectives:

1. Investigate the effect of obstacles on the PDR.
2. Compare the performance of all the competent protocols in the existence of obstacles. The comparison is done in terms of the PDR, the number of elected CHs, the energy consumption and the average number of unclustered nodes per round.

We consider two cases to investigate the effect of the obstacles on the PDR. In the first case, we assume that there is a LOS between all the sensors and that there are no obstacles in the rolling field. For this case, the log-normal shadow fading model is used to calculate the path loss and we refer to the proposed protocol as the NSGA-LOS-CH protocol. In the second case, we use the provided elevation data to find the obstacles in the field and we use the proposed obstacle-aware path loss model. For this case, we refer to the proposed protocol as the NSGA-NLOS-CH protocol. Figure 63 shows the PDR for both

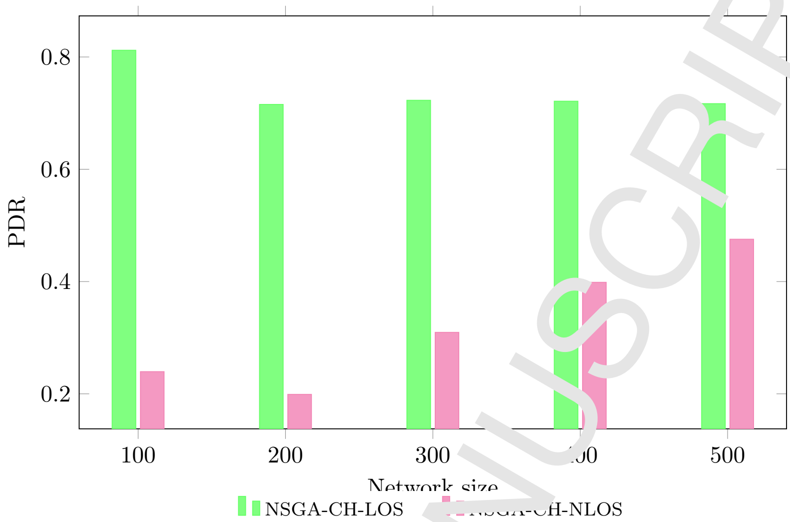

Figure 4: Effect of obstacles on the PDR with and without LOS

of these cases.

It is clearly shown that ignoring the effect of the obstacles, as in the case of NSGA-CH-LOS, can lead to more optimistic PDR values. It is also noted that the PDR of NSGA-CH-NLOS increases with the increase in the number of sensors. Increasing the number of sensors in the same network field area leads to constructing shorter links for communication with a lower probability of obstacles that could interfere those links.

Next, the performance of all the competent protocols is compared in the existence of obstacles. Figure 63 shows the PDR for all the protocols. It is clearly shown that NSGA-CH-NLOS outperforms the other protocols in terms of the PDR. This is due to the fact that NSGA-CH-NLOS clusters the network based on the RSSI values that are derived from the proposed path loss model. This leads to creating clusters that are adapted for the field profile. While PSO-CH uses the RSSI values as criteria for clustering the network, the way the RSSI is calculated does not take into consideration the obstacles in the field.

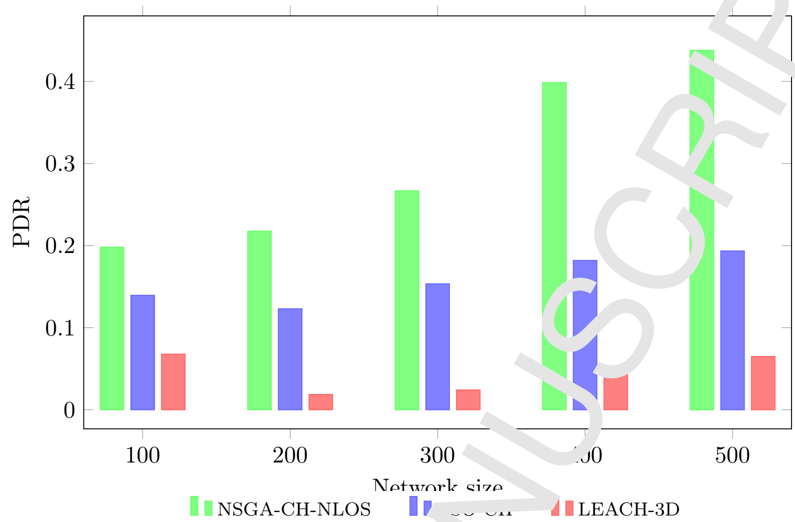

Figure 5: PDR comparison of various protocols in the presence of obstacles

LEACH-3D uses a totally random mechanism when electing the CHs and this, in turn, does not guarantee a high PDR.

Figure 63 shows the average number of CHs per round for all the protocols. It is noted that the NSGA-CH-NLOS protocol results in a higher number of CHs. Unlike PSO-CH, the number of CHs in NSGA-CH-NLOS is variable. Moreover, NSGA-CH-NLOS uses a Pareto-based approach to optimize all of its objectives concurrently. In the existence of obstacles, a higher number of CHs needs to cluster the whole network in order to achieve the scalability objective.

The average consumed energy per sensor is shown in Figure 63. NSGA-CH-NLOS has a slightly higher energy consumption than that of PSO-CH because NSGA-CH-NLOS elects a higher number of CHs as shown in Figure 63. These CHs have to stay active during the whole round which leads to a higher level of energy consumption. On the other hand, LEACH-3D has a very high energy consumption level. Experimental results have shown that LEACH-3D results in a very high number of unclustered sensors. These unclustered sensors stay

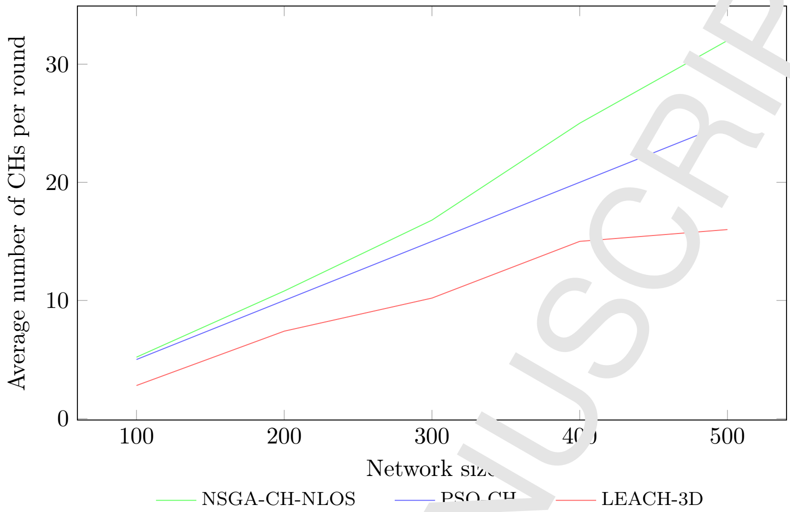

Figure 6: Average number of CHs per round

active during the whole round and consume more energy. On the other hand, both NSGA-CH-NLOS and PSO-CH are able to cluster all the sensors. The average number of unclustered sensors per round is shown in Figure 63.

6. Conclusions and Future work

Data delivery reliability and coverage ratio are considered as key requirements in WSNs. Achieving such requirements in a 3D WSNs with a rolling network field is a challenging problem due to the obstacles that may exist in the field. Moreover, many of the current WSN research is constrained by ideal and optimistic path loss models which are also assumed by most WSN simulators. In this paper, we adopt an obstacle-aware path loss model to account for the effect of obstacles in the network field. To locate these obstacles, the 3D rolling field is modelled using the DEM. Based on the adopted path loss model, a coverage-aware cluster head selection protocol, called COACHS, is proposed. Simulation results show that the effect of obstacles on the PDR cannot be ne-

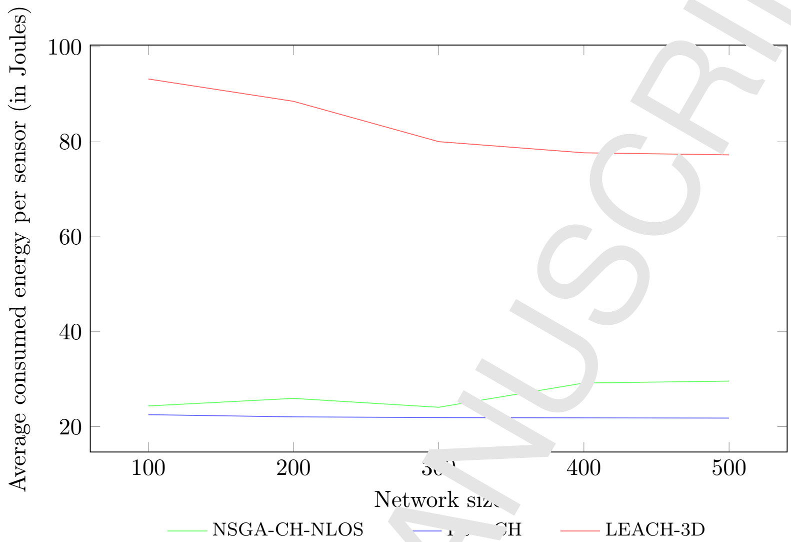

Figure 7: Average consumed energy per sensor

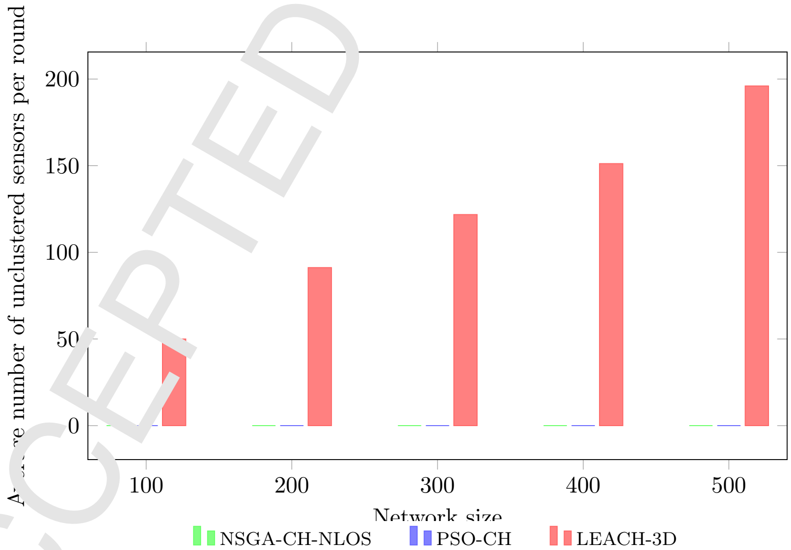

Figure 8: Average number of unclustered sensors per round

glected. Moreover, COACHS outperforms both PSO-CH and LEACH-3D in terms of PDR while maintaining an acceptable energy consumption at the same time.

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