


# Optimization of Sensor Placement for Birds Acoustic Detection in Complex Fields

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**Abstract:** Birds nest in multifunctional semi-natural environments. Intensification of agriculture and forestry prevents their successful breeding, threatening globally their survival. Early bird detection allows for targeted conservation actions, such as local (temporary) habitat protection. The conservationist thus looks for at detecting priority bird species as soon as a territory is occupied, for instance using acoustic surveillance network. We present a comprehensive method to optimize acoustic coverage with a minimum number of sensors in the network. Our method includes a sound propagation model and algorithms for optimized sensor placement. Relevant parameters (e.g., topography, soil type, height of vegetation, weather, etc.) for the sound propagation model are automatically extracted from an area of interest. We implemented and compared Particle Swarm Optimization and Genetic Algorithms-based approaches to solve the optimisation problem.

## 1 INTRODUCTION


Birds breeding in Switzerland occupy forest and farming environments exploited as well for natural resources. The intensive operations on such lands strongly jeopardize their breeding success. Threatened species are for instance the Corncrake (*Crex crex*) or the Eurasian Pygmy-owl (*Glaucidium passerinum*). Early detection, accurate localization, detailed behavioral information and proper policy applications altogether allow to enforce permanent or temporary habitat protection and disturbance avoidance for successful nesting. This paper topic deals with early detection using acoustic network made up of many acoustic sensors in order to survey an area of interest. Two main practical questions arise: how many and where should the sensors be located? Which portion of the area is actually covered (coverage)?

Given an area of interest, the problem of exhaustive bird detection through acoustic sensors is particularly challenging since it requires to precisely model sound propagation in complex and heterogeneous nat-

ural environments. Sound propagation depends on factors such as weather, elevation, type of vegetation, etc. Without the knowledge of the sensors' real detection range (as modified by the above-mentioned factors), either birds are unknowingly missed or the number of acoustic devices to completely cover the area will be excessively high. The main objective of this paper is to present a tool for the optimized configuration of large autonomous acoustic monitoring networks for bird detection.

We propose to model sound propagation according to the ISO 9613-2 standard (ISO 9613-2:1996(F), 1996) and to computationally search for a near-optimal sensor location given a number of available sensors. For this purpose, we implemented particle swarm optimization (PSO) algorithm (Bonyadi and Michalewicz, 2017) and genetic algorithms (GAs) (Whitley, 1994) (detailed information about our methodology is provided in Section 3).

To validate our approach, we developed a tool that, given the geographical coordinates of an area of interest, the number of available sensors and their specifications (such as the detection range), automatically collects all the relevant field information and

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computes a near-optimal solution for the network configuration. For practical use, the tool allows as well manual adaptation of the proposed solution to consider possible unforeseen practical field problems (e.g., a sensor's computed location is inaccessible or on a private land).

This paper is structured as follow: Section 2 presents the state of the art concerning the modeling of sound propagation, the theories supporting near-optimal sensor placement, and computational methods to solve such a problem; Section 3 details the sound propagation model we adopted (i.e., ISO 9613-2), the sensor placement algorithm, the architecture of our system and how we adapted PSO and GAs approaches for our coverage problem; Section 4 presents and discusses the results. Finally, in Section 5, we present the limitations and outlooks of our work.

## 2 STATE OF THE ART

To the best of our knowledge, no systematic and rigorous method for deploying acoustic monitoring networks for ornithology has been yet developed. Such a method implies two main tasks: 1) describing how the sound travel in a heterogeneous landscape and 2) how to use this information to place the sensors in the field in order to minimize the probability of undetected sound.

In this section, we briefly present recent works on sound propagation models, probabilistic theory of sensor placement and acoustic coverage optimisation methods.

### 2.1 Sound Propagation

Modeling the propagation of sound is a complex problem that depends on many parameters such as the frequency and sound pressure at the source, the meteorological conditions, the nature of the ground and the obstacles encountered by the sound or the relief. Taking into account all these parameters implies in return to account for physical phenomena such as reflection and diffraction of sound waves, wind speed profiles and turbulence, geometric dispersion or absorption of sound energy by atmospheric molecules.

Analytical and numerical approaches have been developed and applied in order to tackle the problem of sound propagation. Selection of one approach mainly depends on the complexity of the particular situation as well as on the computer resources available.

Analytical methods are often based on geometrical acoustics and are therefore relevant for simple situations involving an homogeneous and isotropic atmosphere, an homogeneous ground and a zero or constant vertical gradient of sound speed (Attenborough et al., 1980; de Hoop et al., 2005). Geometrical acoustics relies on the ray tracing theory that assumes sound to be a large number of very narrow beams propagating in a straight light unless it encounters an obstacle or a change in the medium of propagation. Propagation above a mixed ground is more complex and has also been studied using Green formulation (Chandler-Wilde and Hothersall, 1985).

In the last few years, propagation of sound in complex fields including heterogeneous grounds and meteorological events has been widely studied. The developed numerical methods have also been compared with the analytical approaches and with field measurements.

The Fast Field Program (FFP) is a computational technique involving the Hankel transformation of the Helmholtz equation in circular cylindrical coordinates and the integration of the resulting ordinary differential equation by analogy with electrical transmission lines (Raspet et al., 1985).

Boundary Elements Methods (BEM) approximates the solutions of partial differential equation implied in the sound propagation by looking at their solutions at the boundaries of the discretized elements of the space. The accuracy of these methods has been well validated against other numerical models (Lam and Monazzam, 2006).

The Transmission Line Matrix method (TLM) (Guillaume et al., 2014) or the Meteo-BEM (Premat and Gabillet, 2000) provide other examples of numerical methods that have been applied to sound propagation.

Nevertheless, these numerical approaches are time and computer resources consuming. Moreover, their implementation becomes very fastidious when considering complex environments, mixed influence of terrain topography and time-dependent atmospheric conditions. An alternative is to consider in an incremental way the different contributions (geometrical dispersion, atmospheric absorption, ground effects, etc.) to sound attenuation and to subtract them from the sound pressure at the source. This is the method supported by the International Organisation for Standardization (ISO) which is commonly used in engineering (ISO 9613-2:1996(F), 1996).

## 2.2 Theory of Sensor Placement

A key question in the field of acoustic network detection is where one should place the sensors in order to maximize the chance of detecting the event of interest, in our case a bird song. There are different approaches to tackle this question.

One possible approach is to assume that sensors have a fixed sensing radius and to solve the task as an instance of the art-gallery problem (González-Banos, 2001). The problem with this approach is that the geometrical assumption is too strong and cannot successfully be applied in very complex field where the sensing range is not constant and depends on local environmental conditions. An alternative approach from spatial statistics (Caselton and Zidek, 1984) assumes weaker geometrical assumptions. It relies on a pilot deployment or expert knowledge to train a gaussian process model that allows for localization predictions made over the sensed field. The model can then be used to predict the effect of placing sensors at particular locations, and thus optimize their positions. For a given gaussian process model, different criteria can be proposed to find the optimal sensor placement. A criteria that is often used is entropy: highest entropy corresponds to regions where the sensors are most uncertain about each other's measurements. The typical sensor placement technique is to greedily add sensors where the entropy is maximal (Cressie and Moores, 2021). However, in our case, the entropy criteria does not seem to be relevant since the set of sensors is then characterized by sensor locations that are as far as possible from each others. This results in sensors distributed at the border of the region of interest (Ramakrishnan et al., 2005).

In (Krause et al., 2008), the authors present a greedy-heuristic method based on maximizing the mutual information between the chosen location and those which are not selected yet. This approach has then successfully been applied for determining near-optimal placement of acoustic devices for monitoring wildlife resources and for localization of sound sources (Piña-Covarrubias et al., 2019).

## 2.3 Particle Swarm Optimization and Genetic Algorithms for Mathematical Optimization in Sensor Networks

Mathematical optimization consists in the selection of the best element in the space of possible solutions (Yang, 2008). The elements are ranked via an objective function (also called fitness function, loss func-

tion or cost function, depending on the context and goals). The space of possible solution is typically limited by some constraints. Many methods exist to find optimal or pseudo-optimal solutions. In this work, we use and compare two approaches: particle swarm optimization (PSO) and genetic algorithms (GAs).

PSO (Kennedy and Eberhart, 1995) is a computational method used in many domains (Bonyadi and Michalewicz, 2017) that aims to solve iteratively an optimization problem by "moving" a population of possible solutions, called "particles", in the space of possible solutions. Simple mathematical formulas manage each particle's position and velocity. Each particle is "attracted" in a direction that depends on the position of its personal (or local) best and the position of the current global best discovered by the swarm (any particle). This is expected to move the swarm towards the best solutions. A good combination of hyper-parameters such as number of iterations, number of particles, inertia weight, acceleration coefficients, etc. is very important to cover the full space of possible solutions and to converge while avoiding local optima.

GAs (Whitley, 1994) is a family of computational methods that aim to solve iteratively an optimization problem by following a process inspired by Charles Darwin's theory of natural selection. The main idea is to select from the population (i.e., a large group of possible solutions) the best individuals and mixing their "chromosomes" (i.e., their features) in a smart way to generate an improved second generation. Generation by generation, the algorithm should converge to the global optimum. A good combination of hyper-parameters such as number of generations, the population size, methods used for the selection, modification and transmission of the chromosomes (crossover, recombination and mutation) may help the algorithm to converge while avoiding local optima.

In an abstract way, it is possible to see PSO as a particular case of GAs, in which the swarm size corresponds to the population size and the logic used to compute the particles displacement corresponds to particular crossover and mutation strategies.

Since more than 20 years, PSO and GAs have been proposed to solve node placement problems in Wireless Sensor Networks (WSN). In (Younis and Akkaya, 2008) (2008), Younis and Akkaya presented a survey about strategies and techniques for node placement in WSN. Their survey is very broad, covering the problem of maximal coverage of the monitored area (with the lower number of sensors). However, they clearly present how the choice of the deployment scheme depends on the application, the topology of sensors, and the environment. They sug-

gest to prefer deterministic approaches when sensors are expensive or when their performances are directly impacted by their position as in our case. Concerning PSO, (Kulkarni and Venayagamoorthy, 2010) presents a survey about the use of PSO for the placement of stationary and mobile nodes, along with other PSO based solutions for WSN problems such as data aggregation, node localization and energy-aware clustering. They showed that PSO is a suitable approach to solve optimization problems in WSNs due to “its simplicity, high quality of solution, fast convergence, and insignificant computational burden”. However, they also raise awareness about its limitations for high-speed real-time applications given the iterative nature of PSO.

GAs have been successfully applied in many contexts (machine learning, scheduling, placement) and domains (engineering, biology, and medicine) (Aybars, 2008). In 2020, ZainEldin et al. (ZainEldin et al., 2020) presented a comparison between different state-of-the-art GA-based techniques used for placement of WSN. In their analysis, they classified algorithms according to three aspects: coverage, connectivity and minimum number of nodes. Most of the approaches proposed successfully achieved full coverage while minimizing cost (e.g., the number of deployed sensors). However, they did not all consider all the three aspects and most of them developed fitness functions and crossover approaches specific for their problem. In our work, we focus on the coverage problem while taking into account outdoor environment factors such as elevation, vegetation height and density, average weather conditions, etc. In this same direction, (Pal et al., 2021) recently faced similar challenges for the deployment of sensor nodes communicating under IEEE 802.15.4 wireless standard. They successfully build a reliable WSN for crop monitoring, but their focus was more to keep connectivity between sensors than on coverage aspects.

### 3 METHODOLOGY

#### 3.1 Sound Propagation Model

Concerning the sound propagation model and for the sensor placement algorithm (see Section 3.2), we adopt the methodology from (Piña-Covarrubias et al., 2019). Since these different elements of the model are separately implemented in our algorithm, they can easily be changed or improved in further developments.

We use fundamental equations according to ISO 9613-2 (ISO 9613-2:1996(F), 1996). We need to cal-

culate the sound pressure  $L_P$  in decibels at the position of the sensor as a function of the sound pressure  $L_W$  at the emitter, possible corrections  $D$  due to the directivity of the source and some attenuation factors  $A_i$  of the sound between the source and the sensor:

$$L_P = L_W + D - \sum_i A_i \quad (1)$$

Since we consider the sound sources as emitting with no preferred direction,  $D = 0$  dB. The attenuation factors  $A_i$  may depend on the frequency of the sound. The first of these factors  $A_1$  comes from the geometrical spreading of the sound into space. It depends on the distance  $d$  between the source and the sensor and of some reference distance  $d_0$  set to 1 m:

$$A_1 = 20 \log \left( \frac{d}{d_0} \right) + 11 \quad (2)$$

The second factor  $A_2$  is a consequence of atmospheric attenuation which converts sound energy into heat. It depends strongly on the distance  $d$ , the sound frequency and some meteorological parameters like humidity and air temperature. Therefore

$$A_2 = \alpha d \quad (3)$$

where  $\alpha$  is a coefficient that takes into account these dependencies. The third factor  $A_3$  is the ground effect because of the reflections of the sound on the ground. It can be written as

$$A_3 = A_s + A_r + A_m \quad (4)$$

where  $A_s$ ,  $A_r$  and  $A_m$  are specific contributions to the ground attenuation at the source, at the receiver and in an intermediate position, respectively.

The fourth one,  $A_4$ , is the attenuation occurring in the presence of vegetation. In accordance with the ISO 9613-2 standard, it depends strongly on the frequency and on the distance  $d_f$  travelled by the sound in the vegetation. Attenuation from vegetation contributes in a limited way to the overall attenuation. Typical values are of the order 1-2 dB. Some corrections  $C_{weather}$  from the meteorological conditions are also taken into account. But as it is emphasized in (ISO9613-2:1996(F), 1996), experience shows that those corrections are, in practice, limited to the range from 0 to about 5 dB and values above 2 dB are exceptional.

Figure 1 shows the effects of each attenuation on a given sound as the distance increases.  $A_1$  due to geometrical spreading of sound is by far the most important contribution to the sound attenuation.

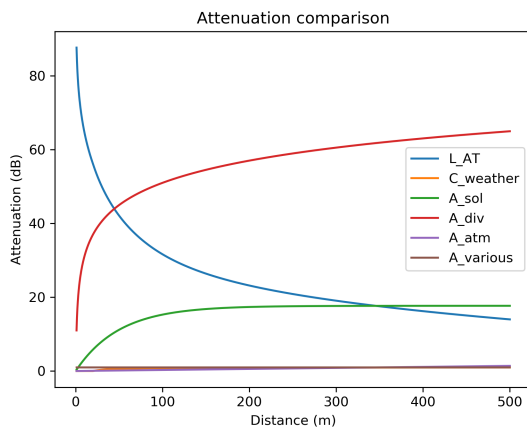


Figure 1: Comparison of the different attenuation contributions to sound intensity. Here,  $L_{AT}$  is the overall sound attenuation ( $L_P$  in equation (1)),  $A_{sol} = A_S$  is the ground attenuation,  $A_{div} = A_1$  the geometrical spreading,  $A_{atm} = A_2$  the atmospheric absorption and  $A_{various}$  the other less significant attenuation factors.

### 3.2 Sensor Placement Algorithm

We present here the main results of the sensor placement algorithm developed in (Piña-Covarrubias et al., 2019) and that we adapted in our system. A given region is considered with a set  $\mathcal{G}$  of possible sound sources and a set  $\mathcal{D}$  of possible sensor placements. The goal of this approach is to *minimize* the probability of *not* detecting a sound emitted somewhere in  $\mathcal{G}$ . The probability of detecting a sound that occurs at any location  $i \in \mathcal{G}$  when a single sensor is deployed at location  $j \in \mathcal{D}$  is given by

$$P_{\mathcal{D}}^j = \sum_{i \in \mathcal{G}} P_{\mathcal{G}}^j P_{\mathcal{D}}^{i,j} \quad (5)$$

where  $P_{\mathcal{D}}^{i,j}$  is a function depending on the sound pressure level detected at  $j \in \mathcal{D}$  of a sound emitted at  $i \in \mathcal{G}$ . The sound pressure is computed with the method described in Section 3.1. If  $n$  devices are deployed on a set of possible locations  $\mathcal{N}$ , the probability of at least one sensor detecting a sound occurring at any location in  $\mathcal{G}$  is

$$P_{\mathcal{D}}^{\mathcal{N}} = 1 - \sum_{i \in \mathcal{G}} P_{\mathcal{G}}^i \prod_{j \in \mathcal{N}} 1 - P_{\mathcal{D}}^{i,j}. \quad (6)$$

Equation (6) assumes independent sound detection by each sensor.

The algorithm then proceeds by iterative greedy placement of the  $n$  sensors in order to maximize the probability  $P_{\mathcal{D}}^{\mathcal{N}}$  in Equation (6). In case  $n = 1$ , the problem is easily solved by choosing the single location in  $\mathcal{D}$  that maximizes the probability, but for  $n \geq 1$

the problem is more complex. It becomes then combinatorial in the sense that the algorithm has to evaluate the probability for  $n$  locations over all the set of possible locations in  $\mathcal{D}$ . The iteration allocates the first of the  $n$  sensors for which the probability of not missing a sound is the highest (or, in other terms, it places the sensor that minimizes the probability of missing a rare sound). Then, at each iteration, it finds the optimal location for the next sensor given the position of the previously placed ones. The result from this greedy approach has been proved to be close to the optimal placement (Krause et al., 2008).

Once the optimal sensor placement has been determined, the next step consists in the sound localization. Considering a subset of the deployed sensor at locations  $\mathcal{N}_{\mathcal{D}} \in \mathcal{N}$ . If one or more of these sensors detect the sound, while the others at locations  $\mathcal{N} \setminus \mathcal{N}_{\mathcal{D}}$  fail to detect the sound, the likelihood that these observations were caused by a sound emitted at location  $i \in \mathcal{G}$  is

$$\mathcal{L}_{\mathcal{D}}^i = \prod_{j \in \mathcal{N}_{\mathcal{D}}} P_{\mathcal{D}}^{i,j} \times \prod_{j \in \mathcal{N} \setminus \mathcal{N}_{\mathcal{D}}} 1 - P_{\mathcal{D}}^{i,j} \quad (7)$$

Given that and using Bayes' theorem, the posterior probability  $P_{\mathcal{G}}^i$  that the sound was emitted at location  $i$  is

$$P_{\mathcal{G}}^i = \frac{P_{\mathcal{G}}^i \mathcal{L}_{\mathcal{D}}^i}{\sum_{i \in \mathcal{G}} P_{\mathcal{G}}^i \mathcal{L}_{\mathcal{D}}^i} \quad (8)$$

If more that one sensors detects the sounds and the time of each detection is available, then it is possible to extend the analysis and to refine the model proposed using Equation (8). However, this has not been implemented yet in our algorithm and the details of the enlarged procedure are explained in (Piña-Covarrubias et al., 2019).

### 3.3 System Description

In order to find the best sensors locations, a user has to provide to the system information such as the region of interest, the sensors' specifications and the characteristics of the targeted species: where the bird sings (on the ground, while flying, in the bushes, etc.), the sound frequency (Hz) and the average sound pressure level at the source (dB).

As explained in Section 3.1, the sound propagation model requires information about the topography, vegetation height/type (fields, forest, bushes, etc.) and the meteorological conditions on site. This information is used to define the probability matrix for all possible sound sources  $\mathcal{G}$  (see Section 3.4). Once defined the perimeter of the region of interest (in terms of

latitude-longitude coordinates), the system automatically gathers all the information required for the computation.

The first source of information is Swisstopo (Federal Office of Topography, 2021). Available data on topography and vegetation have a resolution of half a meter. The second source is IDAweb from MétéoSwiss (Swiss Federal Office of Meteorology and Climatology) providing data collected by ground stations. Concerning the weather data, since the sensors have to remain on site for long time intervals, we use monthly-averaged temperature, humidity and pressure.

Given this information, our tool provides the estimated best location in which to place the sensors and the expected coverage. Finally, even if our tool is not yet intended for the use of general public, we developed a minimal user interface that allows manually changing the position of each sensors, recomputing “on-the-fly” the expected coverage. This allows considering possible difficulties encountered in the field such as unreachable areas, unexpected noisy environments, etc.

### 3.4 Optimisation Algorithms: Concept and Implementation

The main idea of our work is to combine the algorithm proposed in Section 3.2 (Piña-Covarrubias et al., 2019) with the computational mathematical optimization methods presented in Section 2.3 while using the ISO 9613-2 sound propagation model (Section 3.1).

In the first step, the information contained in the map (elevation, vegetation height, weather, etc.) are combined with information coming from the bird profile. This operation provides a probability matrix that covers all the area and it models the probability distribution of the presence of a given species of birds (it corresponds to  $P_G$  in Equations (5) and (6)). The specifications of the sensors (e.g., sensibility, height from ground, etc.) and the ISO 9613-2 sound propagation model are then used to compute  $P_D^{\mathcal{N}}$  in Equation (6). As mentioned above, given a particular sensor placement,  $P_D^{\mathcal{N}}$  represents the probability of *missing* a rare sound (in our case, a bird singing). This function represents the core of the fitness function that our algorithms will try to minimize.

As introduced above, in this work we used and compared PSO and GAs.

Concerning PSO, we used the standard formulation with constraints support as implemented in the *pyswarm* library (tisimst, 2015). We determined hyper-parameters such as *swarm size*, *max iterations*,

$\omega$ ,  $\phi_p$ , and  $\phi_g$  in a validation set composed of test maps close but not overlapping the regions of interest.  $\omega$ ,  $\phi_p$  and  $\phi_g$  represent “exploration versus exploitation” parameters. They indicate the velocity of each particle and the weight given by each particle to the particle’s best known-position (current personal best) and the swarm best-known position (current global best) in order to compute their position at the next iteration. In our problem, each particle represents the possible placement of a sensors in the map. When the algorithm converges or after the maximum number of allowed iterations (indicated by the parameter *max iterations*), we select the swarm’s best-known position as the position in which to place the sensor. With this approach, sensors can be placed one after the other to reach the desired number of sensors or, possibly, until the fitness function does not overcome a given threshold. As a variant, we implemented a “non-greedy” version of the same algorithm in which we could place the  $n$  sensors at the same time. In the greedy algorithm, once a sensor is placed, it cannot be moved anymore, limiting the possibility to converge to the actual global maximum that considers all the sensors at once. In the second, non-greedy variant, each particle represents the positioning of  $n$  sensors at once. Our hypothesis is that it should not suffer of the same limitation and converge to a better global optimization. However, the problem that has to be solved in each iteration becomes increasingly complex (depending on the number of sensors to place at once), therefore we expect to get better performance but only after longer execution time.

Concerning the GAs, we needed an additional step to formulate the problem in a way that could be solved by an evolutionary approach. In particular, we needed to define what represents an individual (or a chromosome) and, subsequently, the mathematical way to implement crossover, recombination and mutation.

We considered an individual as a sensor positioned on the map. The individual’s chromosome represents its coordinates  $x$ ,  $y$ . The population represents a set of individuals (i.e., a set of possible sensor’s placement on the map). From the initial population, we need to select the best elements that will go through the crossover phase. To do this, we used the approach known as “tournament selection”. This method consists of randomly selecting a few individuals and, among them, selecting those with a better score in terms of the chosen fitness function (the “winners” of the tournament). This process is repeated many times and the winners of each tournament are designated for crossover. During crossover, two individuals are selected at a time and they will generate two new individuals of the next generation.



Figure 2: Region used for the test. As reference, the position of orange point visible in the figure above is at coordinates (46.972281 N, 6.704513 E).

The crossover function we implemented consists in a weighted average among the chromosomes (i.e., the coordinates) of the two parents, in which the weights are random values between 0 and 1. In other terms, this means that the offspring is placed in a random position along a vector joining the two parents. Finally, the offspring has a given probability to present mutations. Mutations are typically used to avoid local maxima. In our case, a mutation consists in a random offset along  $x$  and/or  $y$  that we added to the offspring. Once the mutation step is completed, we have a new generation of individuals and the whole process is repeated for a fixed number of generations. From this perspective, it is easy to see the correspondence between swarm size in PSO and population size in GAs, number of iterations (PSO) and number of generations (GAs). We kept these parameters consistent between the two approaches in order to get more comparable results.

### 4 RESULTS AND DISCUSSION

To test and compare PSO’s and GAs’ “greedy” and “non-greedy” versions, we used an area of one square kilometer (Figure 2). We tested with up to 20 sensors to evaluate the evolution of performance in terms of coverage and time when increasing the number of sensors. As the algorithms use random initialization and may converge to different local optima after each execution, we repeated each test 10 times and we averaged the scores.

Table 1 presents a comparison between greedy and non-greedy approaches using our PSO and GAs setups. The test was carried out on the region specified on Figure 2. The scores in the table represent:

Table 1: Comparison of versions and algorithms. Here, the coverage represents the probability to detect a sound.

Number of sensors	Greedy				Non-greedy			
	PSO		Genetic		PSO		Genetic	
	coverage	time (min)	coverage	time (min)	coverage	time (min)	coverage	time (min)
3	51%	33	50%	20	49%	45	46%	29
4	61%	39	59%	25	60%	58	53%	33
5	69%	45	68%	29	65%	70	64%	42

- The overall coverage. It represents the probability to detect a sound. It is computed as the ratio between the surface covered by the sensors and the total surface, while considering the probability of a sound to be emitted in each given point.
- The execution time. As a reference, all computations were done on the same machine and without other applications running: CPU: 3.60 GHz, RAM: 32 GB, OS: Windows 10.

Figure 3 presents the optimal sensors placement for three sensors found by greedy genetic algorithm on the region of Figure 2. As expected, the constant 133 dB sound pressure level (blue line) is closer to a circular geometry around the sensor in case of an homogeneous floor and topography (e.g., the third sensor at the bottom right on Figure 3).

Moreover, in this precise case, the target bird species is known not to live in forest environments. Therefore, the forest area present in the region was excluded of the simulation. As shown in Table 1, the coverage for three sensors using the greedy genetic algorithm is about 50% determined in a time of 20 minutes. The coverage with the greedy PSO algorithm

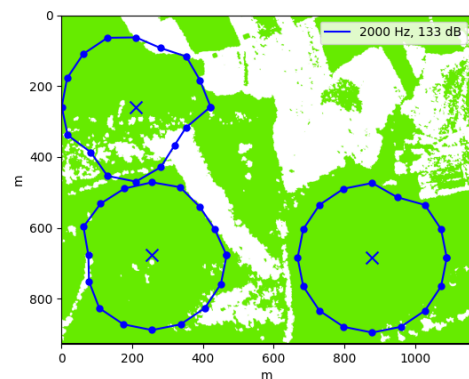


Figure 3: Optimal placement of three sensors. The different background colors are related to the vegetation height. The blue line represents the same sound pressure level. Non circularity around the sensor is due to unequal sound propagation over different floors.

is slightly better with 51%, but the time is then 33 minutes. Taken coverage and time consumption into account lead to the conclusion of a better efficiency for the greedy genetic approach.

It is also relevant to compare our results with a random placement of the sensors in terms of coverage. Results can be seen on Figure 4. Random sensor placement was ran 1000 times and gave a coverage mean value of 26% and a best value of 48% occurring only once. The coverage obtained by our tests presented in Table 1 are all above the random coverage distribution. This result gives an indication on the validity of our different approaches.

As we see from Figures 5 and 6, in general, the non-greedy methods that we proposed take more time and give poorer results compared to greedy methods. In the region of interest, with three sensors deployed, PSO and GAs with greedy method provide a mean coverage above 50%. GAs seems to have a coverage of 1 or 2% below but they take 40% less time. Therefore, the choice of the most suitable algorithm depends on the time available and how good the result has to be. It is also worth mentioning the narrower coverage distribution of the greedy PSO algorithm in comparison with the others ones. This means that through the different runs, the PSO algorithm tended to converge to the same, good solution with low variance. However, the difference with the other approaches remains small, of the order of a few percent. As already emphasized, all approaches are largely better than random placement (Figure 4).

Finally, Figures 7 and 8 show the coverage and time-dependency of the different methods when adding new sensors. Each color line corresponds to the specified algorithm. On Figure 7, the different points on each color line respectively indicate from left to right the coverage for 1 and more sensors. For

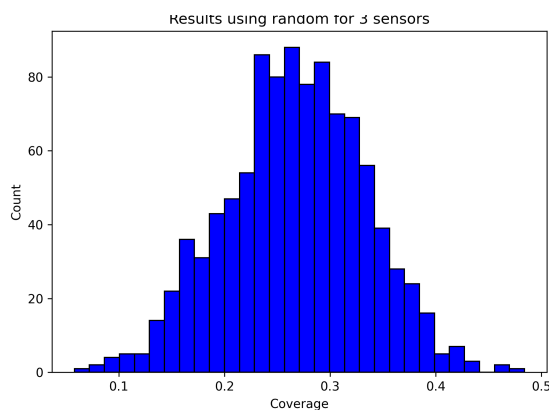


Figure 4: Coverage distribution of random placement. Random placements never reach the coverage of our algorithms presented in Table 1.

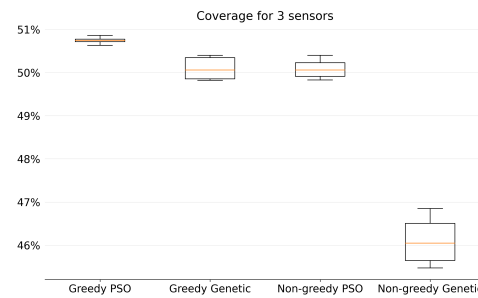


Figure 5: Box plot of the coverage for each method. Mean values can be found in Table 1.

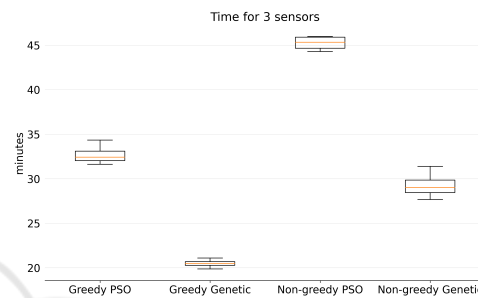


Figure 6: Box plot of the time for each method. Mean values can be found in Table 1.

small numbers of sensors, we see that the coverage still increases significantly. However, as expected, from a certain number of sensors, the region's coverage is reaching its saturation point (close to 100% in our case study) and adding further sensors do not bring any significant improvement while leading to an ever increasing computing time as it can easily be seen from Figure 8. Indeed, with the same presentation, Figure 8 exhibits an "almost linear" time-dependency relative to the number of sensors. Implementing a general method allowing us to find an opti-

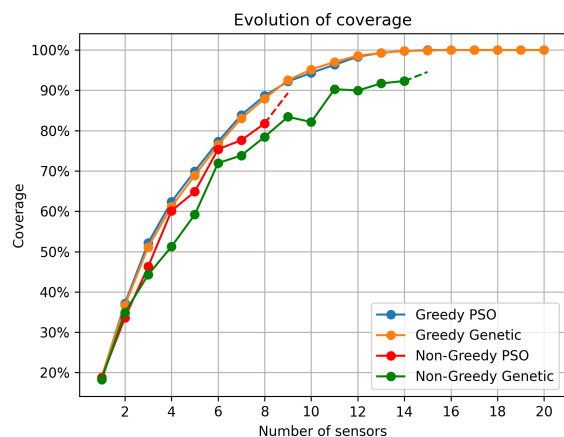


Figure 7: Evolution of coverage for all methods related to number of sensors.



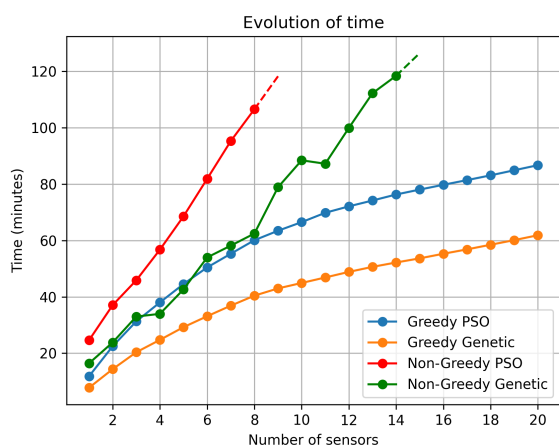


Figure 8: Evolution of time for all methods related to number of sensors.

imum between the number of sensors, the computing time and the coverage will be the subject of further developments. It is furthermore always possible to add one or more sensors in our simulations. But for the practical use of bird conservation for which our system is intended, the number of detectors available is often given by the means of ornithologists and remains limited to a few units.

## 5 CONCLUSIONS

Acoustic recording is a widely used method for bird conservation because of its low-cost. To scale-up this method towards large networks, one central issue is how to configure the network for the best coverage and the lowest number of recording devices. We have developed a practical configuration method suitable for various realistic situations. This method provides a high level of confidence on the true acoustic coverage, which is particularly relevant in order to demonstrate bird absence or scarcity. As such, this tool entails a strong confidence level with respect to bird occurrence and thus strongly support bird population monitoring and conservation. The proposed solution will be proof tested in the field, using additional control devices within a test network and artificial sounds. The test will also allow to estimate the impact on detection caused by by wind, rain or anthropogenic noise.

Being mostly conceived for urban environments, the ISO 9613-2 sound propagation model allows considering additional aspects such as reflections and barriers. For our application in mostly natural landscapes, the current solution does not integrate these aspects. However, it could be interesting to consider them to increase the accuracy of our model in hybrid

landscapes where nature and buildings are mixed.

The modularity of the proposed architecture easily allows testing the same approaches while swapping one of its components. New sound propagation models can replace or extend the ISO 9613-2 and new algorithms could be tested and compared. For instance, we used a simple PSO implementation while some studies showed that modifications can improve the optimisation outcome (Jakubcová et al., 2014). Recently, Anurag et al. (Anurag et al., 2020) proposed a PSO variant that makes use of the idea of negative velocity to improve 2-D coverage. Their approach seemed to outperform the conventional PSO, in particular with a reduced number of sensors. In the future, it could be interesting to compare such an approach as well as approaches based on completely different techniques (e.g., multi-agent reinforcement learning (Buşoniu et al., 2010)).

Finally, we developed here a method for optimization of sensor placement for bird acoustic detection in complex fields. However, more broadly, this kind of methods can have important applications in problems related to other species conservation, land use planning and noise protection.

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