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RESEARCH ARTICLE

INTELLIGENT MONITORING FOR DETECTIONS AND ESTIMATING RADIOLOGICAL PLUME DISPERSION IN AQUATIC ENVIRONMENTS: RIVERS AND SEAS

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Abstract

This work continues the presentation “INTELLIGENT MONITORING FOR RADIOLOGICAL PLUME DISPERSION ESTIMATION - INTELLIGENT MONITORING FOR RADIOLOGICAL PLUM DISPERSION ESTIMATION,” developed as part of the event hosted by ABDAN at the third edition of the Nuclear Trade & Technology Exchange – NT2E, Brazilian Nuclear Olympics (ONB), Hackapower. The primary objective was to develop a system for monitoring radiological plumes in aquatic environments, using a model based on Gaussian Process Regression (GPR) and Particle Swarm Optimization (PSO). The proposed system aims to estimate radiation dispersion in scenarios where plant systems are unavailable, similar to the Fukushima accident. Given this context, it was necessary to create mobile devices with radiation detection capabilities to provide accurate data on dose rate distribution. The model was developed to predict dose distribution using simulated data from a hypothetical accident and involved the use of LoRaWAN networks for drone communication and a firefly algorithm for signaling areas with different radiation levels. The implementation of GPR utilized the ScikitLearn library, while PSO was applied through the pyswarm library, focusing on optimization based on information entropy. Results indicated that the model successfully reconstructed the dose rate profile with an estimate close to the actual values, although data non-uniformity may have impacted accuracy. The use of drones for data collection proved innovative and effective, enabling real-time analysis and offering a robust solution for radiological monitoring in emergency scenarios. Analysis of radiation permeability variation in different aquatic environments highlighted the importance of adjusting measurements according to water density and composition. In conclusion, the work achieved its goal by developing an intelligent system for radiation dispersion estimation, and future work should explore new scenarios and dynamics to enhance model accuracy in real radiological emergency situations.

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Introduction:-

This work is a continuation of the presentation “MONITORAMENTO INTELIGENTE PARA ESTIMATIVA DE DISPERSÃO DE PLUMA RADIOLÓGICA” developed for the event promoted by ABDAN - Desenvolvimento de AtividadesNucleares, the third edition of the Nuclear Trade & Technology Exchange – NT2E, Brazilian Nuclear Olympics (ONB), Hackapower.

The research presented here focuses on monitoring radiological plumes, considering their dispersion in aqueous environments. The challenge proposed for the initial project consisted of developing a system based on dose analysis for training artificial intelligences, which would be adaptive and grounded in field measurements with data provided by mentors. The system should predict the distribution of radiation dose rates from the dispersion plume, independently of plant systems, meaning in the absence of data from the nuclear facility. This scenario was observed in Fukushima in March 2011, and also in the current situation of the State of Rio Grande do Sul – BR.

The proposed development is justified in a severe accident scenario, where atmospheric dispersion systems (ADS) based on theoretical physical models are not an ideal and reliable approach. Therefore, in the case of an intentional or accidental release of radioactive material, it is essential to know the current and future spatial extent of the contaminant, as well as its location, to provide support to emergency response teams (HUTCHINSON, 2016; ONB 2023).

For this purpose, mobile devices with radiation detection and reading capabilities are necessary. Thus, the need to develop a method capable of performing measurements on radiological plume data and adapting its data-collecting elements in the field to provide a more accurate description of the environmental situation is justified.

With this information in mind, the proposal was to model the scenario, with the general objective of developing a system for predicting radiological doses through field measurements. Using data from hypothetical severe accidents, a model based on Gaussian Process Regression and Particle Swarm Optimization was developed. Additionally, after a literature review, the use of the LoRaWAN network for communication between drones and the use of the firefly swarm algorithm for radiation signaling was proposed.

Theoretical foundation: Gaussian Process Regression

Gaussian Processes are widely used in machine learning (ML), defined as a probabilistic framework for supervised ML, applicable to both regression and classification tasks. A regression algorithm can predict an output value based on known data. Gaussian Process Regression (GPR) can make predictions by incorporating prior knowledge, referred to as kernels, and also offers measures of prediction uncertainty. This latter feature is valuable information for decision-making in environmental monitoring applications (WANG, 2009; NUNES, 2023).

The objective of regression is to fit a function to a set of observed data in order to represent and make predictions at new, unknown data points. In GPR, in addition to the expected values for the function, the respective standard deviations are provided, allowing the generation of infinite functions that can be fitted to a given set of observed data within a confidence interval. Figure 1 shows an example of function fitting to observed data points.

GPR performs regression by defining a probability distribution over this infinite number of functions. The mean of this probability distribution will be the most probable representation of the data (WANG, 2009). Appendix I contains explanations regarding the fitting calculations in GPR applications.

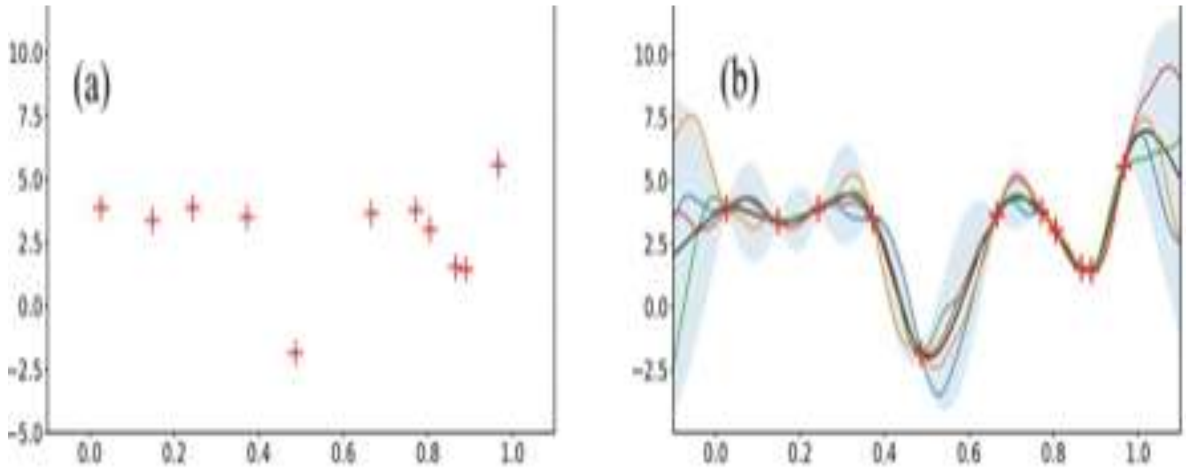

Figure 1:- Example of GPR, where (a) represents the eleven data points and (b) shows five examples of functions that can fit the data.Source : from autors in 2023.

Theoretical foundation: Particle Swarm Optimization

The Particle Swarm Optimization algorithm, or PSO, is part of the category of optimization algorithms based on Swarm Intelligence (SI), a significant branch of optimization techniques aimed at reducing computational demands for complex and large-scale problems, common in various scientific fields (GAD, 2022).

Proposed in 1995 by Kennedy and Eberhart, PSO is a stochastic, particle-based algorithm inspired by the social behavior of animals, such as fish schools and bird flocks in search of food. One advantage of PSO is the presence of few parameters for adjustment. However, this algorithm finds the best solution through the interaction of particles.

Considering PSO as SI, it must satisfy five principles: adaptability, stability, quality, and proximity. Adaptability refers to the particle's ability to change its search behavior when computational cost is too high. Stability implies that the particle should not change its search behavior in response to environmental changes. Quality means the particle must be able to respond to performance measures in the environment. Lastly, proximity refers to the particle's ability to perform time and space-efficient calculations (GAD, 2022).

In PSO, the swarm of particles updates its relative positions from iteration to iteration, guiding the algorithm in the search process. To obtain a potentially optimal solution, each particle moves towards its best personal position achieved so far (p_best) and the swarm's best global position (g_best). Considering a minimization problem, we have:

$$p^{t}_{best_i} = x^{*}_{i} \mid f(x^{*}_{i}) = min_{k=1,2,\dots,t}(\{f(x^{k}_{i})\}) \quad (1)$$

onde $i \in \{1, 2, \dots, N\}$ e

$$g^{t}_{best} = x^{t}_{*} \mid f(x^{t}_{*}) = min_{i=1,2,\dots,N_{k=1,\dots,N}}(\{f(x^{k}_{i})\}) \quad (2)$$

Figure 2:- Characteristic Equation. Source:Source: from autors in 2023.

Where i denotes the particle index, t is the current iteration number, f is the objective function to be optimized (minimized in this case), x is the position vector (or a potential solution), and N is the total number of particles in the swarm. The update of velocity v and position x of each particle i in the current iteration $t + 1$ is given by the following equations:

Where i denotes the particle index, t is the current iteration number, f is the objective function to be optimized (minimized in this case), x is the position vector (or a potential solution), and N is the total number of particles in the swarm. The update of velocity v and position x of each particle i in each current iteration $t + 1$ is given by the following equations:

$$v_i^{t+1} = wv_i^t + c_1 r_1 (p_{best_i}^t - x_i^t) + c_2 r_2 (g_{best}^t - x_i^t) \quad (3)$$
$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (4)$$

Figure 3:- Equation of the Phenomenon. Source : from autors in2023.

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Theoretical foundation: Data Collection Equipment

Considering the severe accident that occurred at the Fukushima nuclear plant in 2011, it was observed that, in addition to the security systems present around the facilities, an external system capable of collecting and analyzing data, especially radiological emissions, is crucial for decision-making support.

In this context, the option fell on small unmanned vehicles, commonly known as drones. These drones can be equipped with various devices, including radiation sensors and locomotion mechanisms.

Given the location of Brazilian nuclear facilities, near the sea, and the high incidence of rivers and water bodies in Brazilian territory, the use of hybrid equipment is proposed, allowing the measurement of deposited doses in aquatic environments.

The implementation of these equipment and methods enables measurements and validations in accordance with current legislation and authorizations, such as the documentation that may be required by the Brazilian Navy, responsible for the monitoring and inspection of vessels.

Theoretical foundation: Transmission of Collected Data

Communication with these underwater drones would be carried out via acoustic communication, which is the most suitable for underwater transmissions due to its long range and relative stability in different water conditions. However, it is important to consider the data transfer rate and the stability of radiation detection. Acoustic communication would send data about the radiological plume every 5 minutes, providing regular and valuable updates for decision-making.

A crucial consideration is whether radiation detection would be compromised by sound interferences. The stability of radiation detection must be ensured, even in the presence of underwater noise, to guarantee measurement accuracy.

In an aquatic environment, acoustic communication is subject to interference from various sound sources, such as marine fauna activity, vessels, and other underwater devices. To ensure the stability of radiation detection, the radiation sensors installed on the drones must be isolated from these sound interferences. This can be achieved through noise filtering technologies and signal processing, which allow distinguishing between acoustic communication signals and potential environmental noise.

Additionally, the accuracy of radiation measurements must be maintained even under adverse conditions. The acoustic communication system must be robust enough to reliably transmit data every 5 minutes, without the integrity of the information being affected by noise. This is especially important for continuous and real-time monitoring of the radiological plume, allowing quick and informed responses from emergency teams.

To ensure this stability, rigorous testing must be conducted in controlled and real environments, simulating different levels of underwater noise. These tests will help calibrate the radiation sensors and adjust the communication and noise filtering algorithms, ensuring the system can operate efficiently under various environmental conditions.

Thus, by incorporating advanced filtering technologies and conducting comprehensive tests, it is possible to ensure that radiation detection by underwater drones maintains high accuracy and stability, even in the presence of underwater sound interferences.

Theoretical foundation: Area Signaling

Considering the scenario of demarcating a radiological plume, the need for visual signaling was identified. Given the use of multiple units (drones) for data collection, analysis, and transmission, the necessity for swarm intelligence capable of performing visible markings in the field was recognized. Therefore, the signaling system to be developed in Python was based on the firefly swarm algorithm.

The firefly swarm algorithm is used for road signaling, which covers a wide area due to its configuration of interrelated individuals without physical connection. It provides a quick response and indication regarding the safety of environments, as the algorithm relates the collected doses to colored LED lights installed on the drones.

For better understanding, let's exemplify the scenario. The radiological plume is dispersing in the environment around the nuclear plant facilities. At this moment, the drones equipped with radiation sensors, colored LEDs, and various communication and data transmission systems are activated according to the safety protocol. These systems may or may not be viable for area demarcation, considering the visibility difference at different depths, as shown in Figure 4 below.

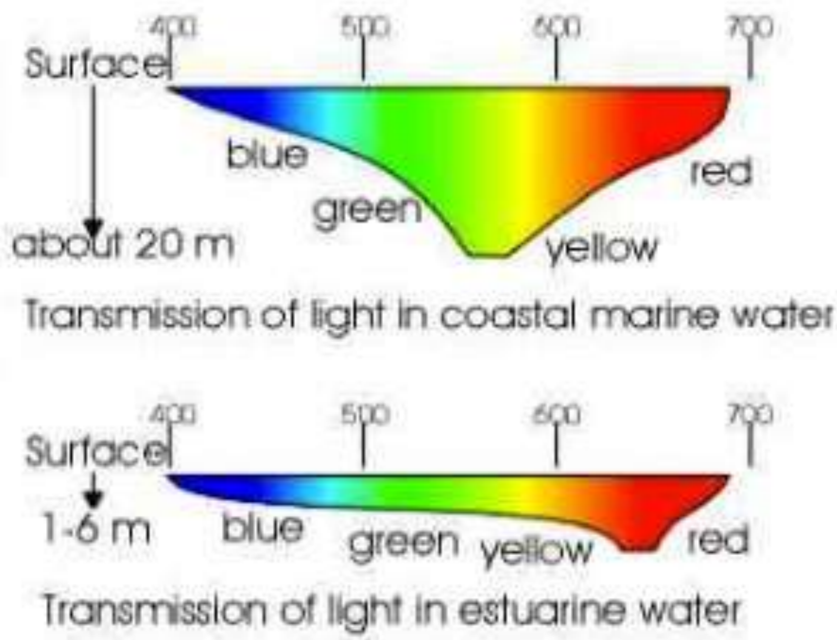


Figure 4:- Depth penetration of colors for area signaling. Source: Malgorzata Wessels née Pietrzykowska in 2015, The roles of Lhcb1 and Lhcb2 in regulation of photosynthetic light harvesting.

In environments where there is no danger regarding the amount of dose to be absorbed by individuals, radiation detection will trigger the emission of steady green lights. In safe locations with safe radiation doses, the drones will activate flashing green lights. Subsequently, in environments with safe radiation doses for exposures of up to 5 hours, yellow lights will be activated. For areas where the exposure should be limited to up to one hour, flashing yellow lights will be activated. In areas where the dose is harmful and possibly fatal for any duration of stay, red LEDs will be activated. The organization of this programming is given by a pseudocode found in FUNDING Appendix II.

Materials and Methods:-

Considering the scenario of severe accidents at nuclear power plants, where no information is available from the plant's systems, it is necessary to use mobile equipment equipped with radiation detectors to estimate dose rate profiles. Additionally, it is essential to ensure intelligent environmental exploration, making the sampling method practical while obtaining useful information, reducing the time needed to aid decision-making.

To this end, a methodology of active machine learning was developed, comprising a Gaussian Process Regression (GPR) optimized by a Particle Swarm Optimization (PSO) algorithm, capable of estimating plume propagation to support decision-making. The pseudocode for this methodology was developed in Python and is found in Appendix III.

For the development of this work, simulated data from a hypothetical severe accident was provided, divided into 18 cycles, each lasting fifteen minutes. Figure 5 shows the dose rate distribution map for cycle 4, referring to 60 minutes after the simulated accident.

Figure 5:- Dose rate distribution map for cycle 4 of the hypothetical accident.

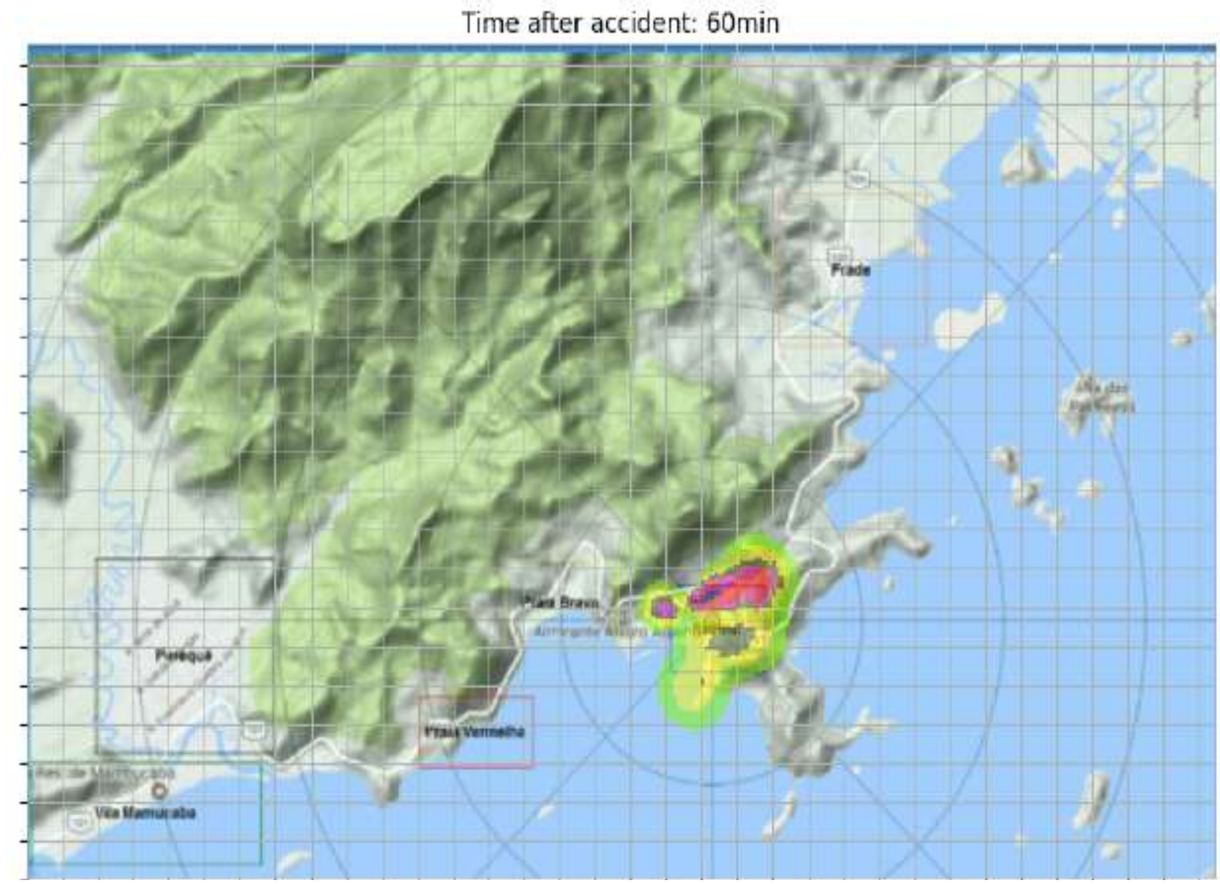


Figure 5: Dose rate distribution map for cycle 4 of the hypothetical accident. Source: from autors in 2023.

The data used was initially reshaped, resulting in a 335 x 215 matrix. Thus, the indices of each value in the matrix correspond to a hypothetical position where the reading occurred. Figure 6 shows the dose distribution profile in three dimensions (Appendix IV contains some of the dose distribution profiles for all simulated cycles), with x1 and x2 as positions and the z-axis representing the recorded dose magnitude (unit µrem/h). This unit is no longer used as the standard for recording equivalent radiation dose, but given the provided values, it was retained as converting would require dealing with very large numbers. Figure 6 presents the dose indices generated based on the matrix in Figure 7, which shows part of the cycle 4 matrix, with the reading value of 4.523067e–08 µrem/h at points x1 = 34 and x2 = 174.

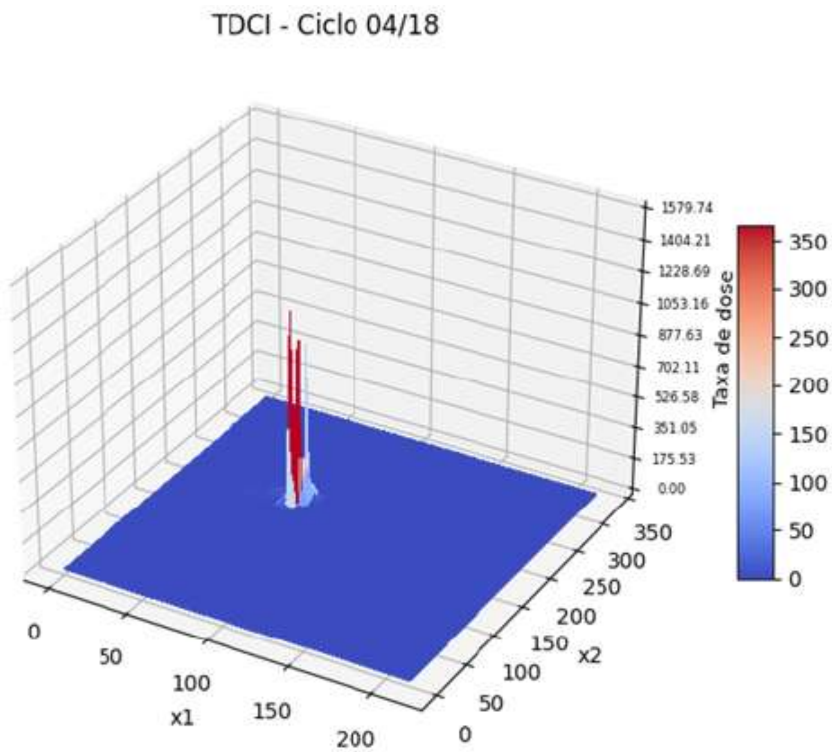


Figure 6:- Dose rate profile for cycle 4, where the maximum point is at x1 = 71 and x2 = 187, with a reading value of 1579.739 µrem/h. Source:from autors in 2023.

	33	34	35	36	37
175	0.0	4.523067e-08	2.208047e-07	7.858757e-07	2.437691e-06
176	0.0	1.564997e-07	8.286012e-07	3.022393e-06	9.497549e-06
177	0.0	4.877575e-07	2.604801e-06	9.538569e-06	3.006115e-05
178	0.0	1.36931e-06	7.373436e-06	2.709061e-05	8.557535e-05
179	0.0	3.462664e-06	1.879683e-05	6.925027e-05	0.0002191242
180	0.0	7.887129e-06	4.315843e-05	0.0001593427	0.0005047417
182	0.0	1.618205e-05	8.927e-05	0.0003301089	0.001046161
183	0.0	2.990568e-05	0.000166382	0.0006159146	0.001951694
184	0.0	4.978327e-05	0.0002795084	0.001035321	0.003278549
185	0.0	7.46497e-05	0.0004233778	0.001568584	0.004961568
186	0.0	0.0001008306	0.0005784834	0.002143093	0.006768257
187	0.0	0.0001226828	0.0007133511	0.002642017	0.008328168

Figure 7:- Visual representation of the matrix for cycle 4 data. Source: from autors in 2023.

For the implementation of the GPR model, the Gaussian Process Regressor function from the ScikitLearn library was used (PEDREGOSA, 2011). For PSO, the pyswarm library was used (PYSWARM, 2023), an evolutionary and gradient-free optimization package for Python that supports constraints. The objective function used in PSO is based on information entropy, as explained by Jorge Mamoru Kobayashi in 2010, guiding the active machine learning process. This function is defined in equation (5), Figure 8.

$$h = -\left(z_{predito} + 0,5 \cdot \log(2\pi \cdot e \cdot |\sigma|)\right) \qquad (5)$$

Figure 8:- Equation 5.Source: from autors in 2023.

Where z is the predicted reading value, and σ is the standard deviation of the predictive distribution at the query points. The kernel used in GPR was the product of the constant kernel, Constant Kernel, with the Radial Basis Function (RBF) kernel. For the Constant Kernel, the default unitary value was used, with fixed value limits. For the RBF, the length scale (l) was set to ten, with fixed length scale limits (PEDREGOSA, 2011).

Additionally, the permeability of radiation in freshwater and saltwater was calculated, considering a temperature range of 10 to 35 degrees Celsius. Radiation attenuation in aqueous media varies significantly between freshwater and saltwater due to the difference in ionic composition and density of the two types of water. In freshwater, permeability is higher, allowing radiation to travel longer distances compared to saltwater, where the presence of salts increases density and consequently, radiation attenuation. These calculations are essential for adjusting GPR measurements and predictions in aquatic environments, ensuring the accuracy of dose estimates even in different water and temperature conditions.

Results And Discussions:-

Proposed Model for Estimating Spatial Distribution of Dose Rates

According to the previously mentioned methodology, the results obtained are represented in the following two images for cycle four only. Figure 9 shows the estimate made by the GPR model, with the maximum point located at $x1 = 84$ and $x2 = 201$. Although this point is close to the actual position, the value found was 0.5644 μrem/h. However, by comparing figures 5 and 10, we can see that the surroundings of the highest dose point were identified, with the estimate showing behavior similar to the actual scenario. It is worth noting that the colors in figure 9 do not represent the same dose reading value as in figure 5.

Considering the data provided for model training, one factor that may have hindered its performance was the non-uniformity of the data, which presented a large number of peaks and valleys corresponding to the supposed measurements in the hypothetical case, affecting the model's convergence (2024, WEI).

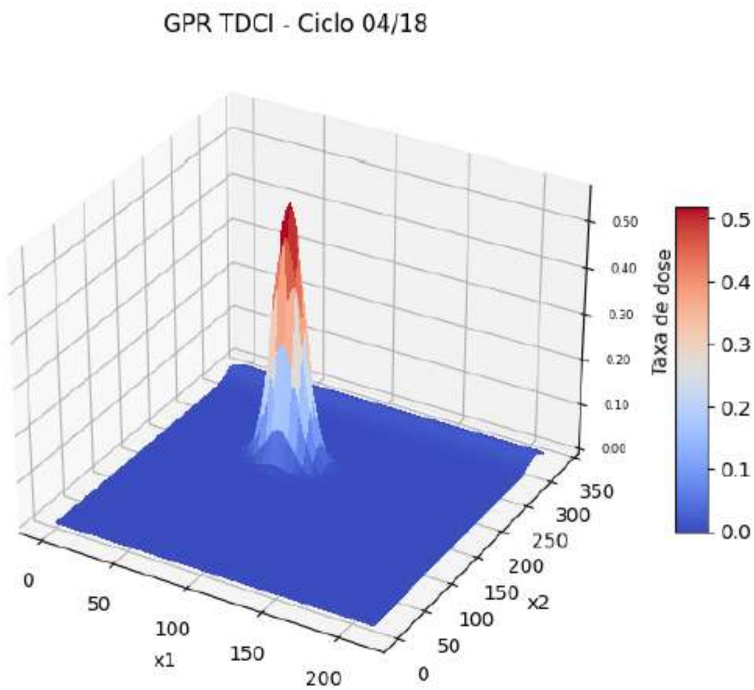


Figure 9: Estimated dose rate profile by the model for cycle 4. This profile estimate was made with 1000 iterations, with the number of particles and the maximum number of PSO iterations both set to 200. Source: from autors in 2023.

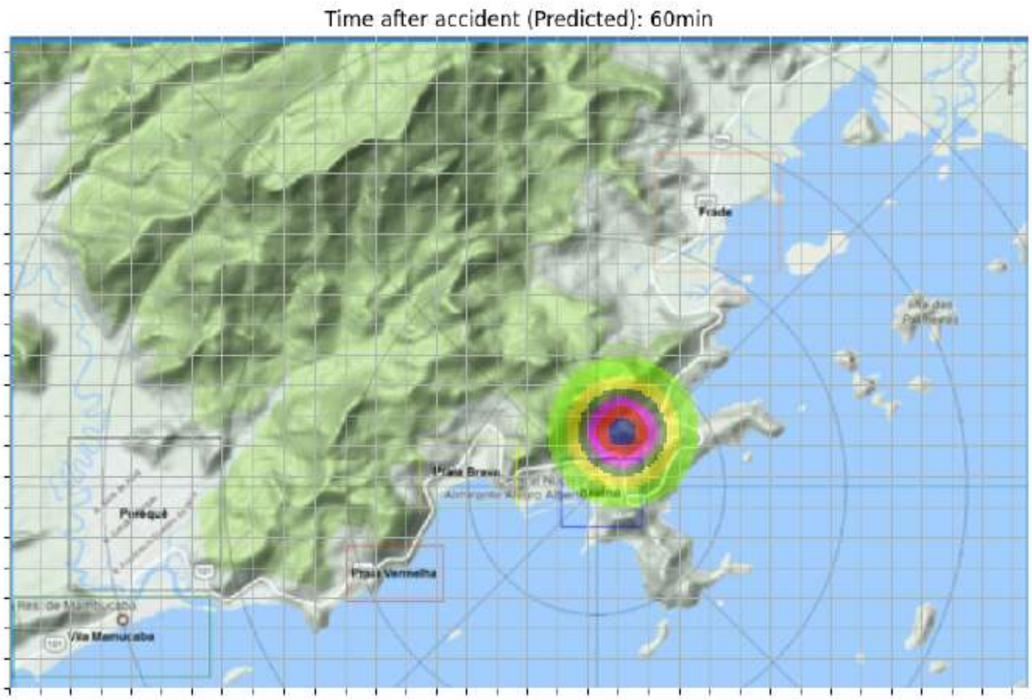


Figure 10:- Dose rate distribution map estimated by the model for cycle 4 of the hypothetical accident. The colors represent the doses on the scale of Figure 8.
Source: from autors in 2023.

Data Collection System

The use of drones as a tool for collecting dose rates from radiological dispersion represents a significant innovation in this field, highlighting their ability to access hard-to-reach areas and potentially hazardous locations, such as radiation-contaminated areas or confined spaces in nuclear facilities. These devices are a valuable technological resource as they can reduce and even eliminate the need for direct human exposure to radiation, significantly improving the safety of professionals involved in data collection.

Drones equipped with radiological sensors can perform real-time measurements, providing immediate information on the dose rate dispersion at a given location. Utilizing acoustic communication, instead of LoRaWAN, these drones can efficiently transmit data even in underwater environments, with frequent updates every 5 minutes. When combined with artificial intelligence, these drones become highly valuable technical-scientific equipment, ensuring the accuracy and stability of measurements even in the presence of underwater noise.

The use of drones offers flexibility and scalability. A single drone can be deployed for routine situations, while multiple units (swarm) can be utilized in emergencies or large-scale installations, enabling broad coverage at different heights and positions within the same plant (DINELLI, 2023). Acoustic communication ensures stable data transmission even in adverse conditions, ensuring that radiation detection is not compromised by acoustic interferences.

The proposal of this work with drones equipped with radiological sensors and acoustic communication for monitoring radiological plumes represents an effective and safe approach to data collection in severe accident scenarios, providing a robust solution for protecting professionals and optimizing emergency responses.

Variation of Data According to the Aquatic Environment

The variation in radiation permeability in different aquatic media and temperature ranges plays a crucial role in the effective monitoring of radiological plumes. Table 1 presents the data that guide the accuracy of dose estimates in aquatic environments, ensuring reliable measurements even under variable conditions.

When considering the use of drones equipped with radiological sensors for data collection in nuclear accident scenarios, it is essential to understand how radiation propagates through water. As shown in the table, radiation permeability varies significantly between freshwater and saltwater, influenced by density and the presence of salts.

From these data, we can observe that radiation has a lower penetration capacity in saltwater compared to freshwater, due to the higher density and the presence of salts, which increase radiation attenuation. This has important implications for the planning and execution of radiological monitoring operations in different types of water bodies.

Therefore, in developing nuclear emergency response strategies, it is crucial to consider not only the technology used, such as drones and machine learning algorithms, but also the characteristics of the environment in which the measurements will be carried out. Understanding the variation in radiation permeability provides valuable insights to ensure the accuracy and reliability of radiological dose estimates in aquatic environments, thereby contributing to a more effective and safe emergency response.

Table 1:- Differential Radiation Permeability According to Water Attenuation.

Temperature (°C)	Radiation Permeability in Fresh Water (m^{-1})	Radiation Permeability in Salt Water (m^{-1})
10	0.95	0.85
15	0.90	0.80
20	0.85	0.75
25	0.80	0.70
30	0.75	0.65
35	0.70	0.60

Authorial, 2023.

Conclusion:-

The work accomplished achieved the expected objective, consisting of the development of an AI-based model to estimate the spatial distribution of dose rates resulting from a severe accident at a nuclear plant, even when plant instruments and systems are unavailable. The proposed model was grounded in the use of external measurements through a swarm of drones equipped with nuclear instrumentation, which were controlled by an AI system. To this end, the concept of active machine learning was adopted, utilizing GPR (Gaussian Process Regression) to reconstruct the dose rate profile, PSO (Particle Swarm Optimization) to optimize the drone movement, and firefly swarm algorithms to delineate regions with varying dose rates.

It was observed that, in the simulated scenarios, the model was capable of adequately reconstructing the dose rate profile for Cycle 4, accurately identifying the high-dose regions. As next steps, it is suggested to explore new hypothetical severe accident scenarios and to consider a dynamic approach to the model to address a real severe accident scenario. These additional actions aim to further enhance the model's capability to provide accurate and reliable estimates of dose rates in radiological emergency situations.

Appendix I – Gpr Adjustment

An ideal fit in a Gaussian Process Regression (GPR) would be represented by a smooth and continuous distribution curve. Therefore, considering this characteristic, it is expected that f(xi)f(x_i)f(xi) and f(xi+1)f(x_{i+1})f(xi+1) are close for two very near points in the set xix_ixi, i.e., there is a relationship xix_ixi and xi+1x_{i+1}xi+1 between f(xi)f(x_i)f(xi) and f(xi+1)f(x_{i+1})f(xi+1). For this behavior to occur, the curve must be a multivariate normal distribution, with a probability density function given by where NNN is the number of dimensions, xxx are the input data, μ\muμ is the mean of the distribution, and KKK is the covariance matrix, which determines how these data relate to each other. The notation representing the multivariate distribution of dimension NNN is where it denotes a multivariate Gaussian distribution (WANG, 2009; NUNES, 2023).

The definition of the covariance matrix KKK, of size N×NN \times NN×N in the aforementioned notation, will be one of the most important parameters to be determined in GPR. The elements of this matrix describe how variables, such as xix_ixi and xjx_jxj, are related. It is expected that when points are close, such as xix_ixi and xi+1x_{i+1}xi+1, or have a significant relationship, the elements Ki(i+1)K_{i(i+1)}Ki(i+1) and Ki(i+2)K_{i(i+2)}Ki(i+2) are numerically similar. In the opposite scenario, it is expected that the coefficients tend to zero. Thus, considering these mentioned characteristics, the covariance matrix will describe both the shape of the distribution and determine the characteristics of the function we aim to predict (WANG, 2009; GÖRTFLER, 2019).

To define the elements of this matrix, various functions can be used, known as kernels or covariance functions. A kernel takes two points as input and returns a measure of similarity between these points in the form of a scalar. Therefore, since this kernel describes the similarity between the values of our function, it controls the possible shape that a fitted function may adopt. Examples of kernels in the literature include: White Noise Kernel (WNK), Radial Basis Function (RBF), Rational Quadratic Kernel (RQK), Periodic Kernel (PK), and Matérn Kernel (MK). Each of the aforementioned examples has its characteristic parameters. The RBF is considered the default kernel for GPR, defined as, where σ2\sigma^2σ2 is the variance and lll is termed as the length scale, which determines the range of influence on neighbors. Increasing this parameter makes points further apart become more correlated (GÖRTFLER, 2019).

Appendix II:- Pseudocode For Light Signaling In Python For Firefly Swarm Intelligence.

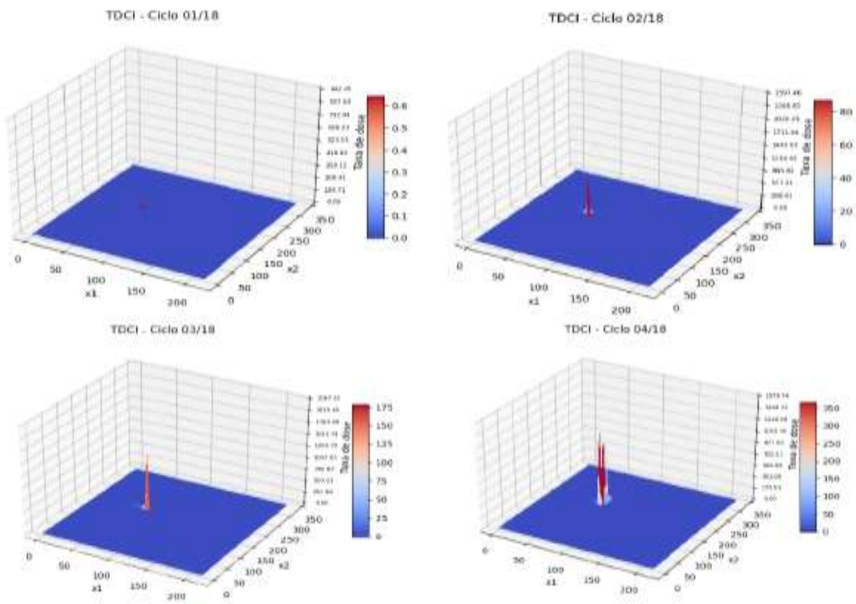
```
python
  Copiar código
  import time
  # Function to determine light color based on radiation exposure
  def define_light_color(radiation_exposure):
    if radiation_exposure<= 0:
      return "steady green"  # Safe location
  elifradiation_exposure<= 1:
      return "blinking green"  # Safe radiation doses
  elifradiation_exposure<= 5:
      return "steady yellow"  # Exposure exceeding 1h
    else:
      return "blinking yellow"  # Exposure exceeding 5h (harmful)
  # Simulation of radiation exposure readings (fictitious values)
  current_exposure = 0  # Example of current exposure
  # Main loop
  while True:
  current_exposure += 0.1  # Example of gradual increase in radiation exposure (for testing)
    # Determine light color based on radiation exposure
  light_color = define_light_color(current_exposure)
    # Update the drone lights according to the determined color
    # Replace this part with actual drone light control code
  print(f"Drone lights: {light_color}")
  time.sleep(1)  # Wait 1 second before updating again
```

Appendix III – Pseudocode; Development Of The System's plume

```
  python
  Copiar código
  x = pos_initial  # Initial position: we define two starting points, each with coordinates x1 and x2
  y = measure_rad()  # Radiation measurement at the starting points
  n_iters = 200  # Number of iterations
  for i in range(n_iters):
    # GPR
    GP = initialize_GPR_model()
  GP.fit(x, y)
  y_pred, sigma = GP.predict(X_real)
    # PSO
  x_optimized, y_optimized = PSO(objective_function)
```

```
    x = x.add(x_optimized)
    y = y.add(measure_rad(x_optimized))
# GPR of the last optimized point
GP = initialize_GPR_model()
GP.fit(x, y)
y_pred, sigma = GP.predict(X_real)
```

Appendix IV – Dose Rate Profiles Of Provided Data



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Author's Contributions
Giulianna dos Santos Pereira was responsible for organizing and managing the core ideas of this research, ensuring the integration of the various components into a cohesive and concise manuscript. Samara Prass dos Santos was responsible for the computational work and testing of the mathematical models. Aparecida Marta Regina dos Santos Pereira contributed by adjusting the analyses and providing insights on detection in aquatic environments. Rodrigo Campos Pereira conducted the tests and studies related to dose dispersion in aquatic environments. Marcus Vinicius Araujo Vieira analyzed viable data transmission methods for the study. Fabiane ModenesaGarbim was responsible for analyzing the artificial intelligence systems most suited to the research. Álvaro José Boareto-Mendes served as a supervisor and reviewer, and Fernando Manuel Araujo-Moreira acted as the senior supervisor and reviewer. All authors have read and approved the final manuscript.

Ethics
The authors confirm that this manuscript complies with the ethical standards of the discipline and the institution(s) involved. No ethical violations were identified during the course of this research.

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