Performance Evaluation of AquaFeL-PSO Informative Path Planner under Different Contamination Profiles

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Abstract The use of Autonomous Surface Vehicles allows streamlining the task of monitoring the water quality parameters of water resources, reducing costs and time spent. In addition, the vehicles are capable of taking water measurements in hard-to-reach areas. This chapter evaluates the performance of the AquaFeL-PSO monitoring system in different contamination profiles. The AquaFeL-PSO is an algorithm based on Particle Swarm Optimization, Gaussian processes and Federated Learning technique. The operation mode of the algorithm is two-phase, the exploration phase, which is responsible for covering the largest possible area of the water resource in order to detect contaminated areas, and the exploitation phase, which is responsible for accurately characterizing the water quality parameters in the contaminated areas. This system is evaluated using different benchmark functions in order to observe the performance of the system under different contamination profiles. The results show that the AquaFeL-PSO was able to generate models of the water quality parameters in eight of the ten contamination profiles. In addition, it had the best performance in detecting pollution peaks and

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generating the model of the water quality parameters of the entire water resource.

Key words: Informative Path Planning, Particle Swarm Optimization, Federated Learning, Autonomous Surface Vehicles, Machine Learning, Water Monitoring, Multi-modal Problems

1 Introduction

Polluted waters can be described as bodies of water that are imbalanced in terms of physico-chemical properties, such as pH level, Dissolved Oxygen (DO), Turbidity, etc [17]. Ecosystems with such conditions can be toxic and even deadly for life. A clear example is the current state of the Ypacarai Lake (Paraguay) [7], where toxic blue-algae blooms during the hot months of summer appear. The eutrophized [3] waters are hazardous for fishes as well as humans, preventing wildlife from flourishing, aquaculture and tourism. Although there are works that focus on recovering the waters via direct treatment[16], the pollution models or contamination profiles are so far left unaddressed, which may lead to inefficient and expensive water treatment.

Contamination profiles are models that show a *contamination level* for each location or coordinate related to a water body [25]. The usefulness of these models is evident since contamination peaks needs more attention and treatment. Therefore, obtaining reliable contamination models and pinpointing contamination peaks are tasks that will provide efficiency in treating or maintaining healthy water bodies. This is the main objective of the present work, and to provide good results the usage of Autonomous Surface Vehicles (ASVs) equipped with Water Quality Parameters (WQP) Sensor systems is proposed. ASVs have been used for WQP measuring since they provide significant advantages when compared to fixed stations and manual measurement campaigns [2, 23].

A coordinator system can efficiently distribute multiple ASVs to cover a water region and measure WQPs. However, as the water models can vary weekly [21], may mean that monitoring missions might be done with few reliable initial information. In that sense, the system will benefit from including gathered data during the mission to decide on the measurement locations, i.e., an online system. Moreover, online missions will be useful for obtaining both good overall contamination models and peak contamination locations. The proposed system focuses on both of these objectives, and therefore, it is divided into in two steps: a first that considers shared information among all the ASVs and a latter stage that federates the learning into promising zones that could contain contamination peaks. The proposed system is called AquaFeL-PSO [8]. In the fist phase, the AquaFeL-PSO generates a baseline WQP model, which is used to determine the areas where contamination levels

are high. In the second phase, the proposed system focuses on characterizing WQP in contaminated areas and detecting pollution peaks with higher resolution.

Noting that the contamination behavior is unknown a-priori, this work extends previous approaches to evaluate the performance of the AquaFeL-PSO considering different benchmark functions, disregarding expected WQP behaviors so that the evaluation of the system is broader. Consequently the main contribution of the present chapter is the evaluation of the AquaFeL-PSO monitoring system in the detection of contamination peaks and in the generation of the model of the WQP of a water resource under different contamination profiles.

The chapter layout is as follows: in Section 2, the related work of path planners for ASVs is presented. The explanation of the monitoring problem and the assumptions of the monitoring system can be found in Section 3. The path planners are explained in Section 4. In the Section 5 the different contamination profiles and comparison metrics are listed, and the experiments and comparisons between path planners are presented. Section 6 provides a summary of the results. A conclusion of the work and future research directions are presented in Section 7.

2 Related Work

Patrolling and monitoring scenarios using autonomous vehicles technology have been studied by several researchers in recent years [3, 29, 17, 23, 24]. Monitoring and patrolling tasks of water resources are performed with ASVs equipped with sensors capable of measuring WQP, like pH, temperature, DO sensors, and with sensors that allow the guidance and control system to know where the vehicle is located and its environment, such as Global Positioning System (GPS), an Inertial Measurement Unit (IMU), a Light Detection and Ranging (LiDAR), among others. Researchers propose machine learning techniques as a solution for the generation of ASV trajectories in order to fulfill the assigned task, techniques such as Genetic Algorithm (GA) [3], Bayesian Optimization (BO) [18], Swarm Intelligence [25], Deep Reinforcement Learning (DRL) [28], etc.

The trajectory generation in [2] is based on a GA, an algorithm based on selection theory of Charles Darwin. In addition, the authors use the Traveling Salesman Problem (TSP) as a monitoring problem. The objective of the monitoring system is to optimize the ASV trajectory and to cover the largest possible area of the water resource. The researchers use the Ypacarai lake as an example scenario, and beacons have been set up for the ASV to pass through. This work is extended in [1], where the monitoring problem changes to the Chinese Postman Problem (CPP). By modeling the monitoring problem as the CPP, the ASV can visit the beacon more than once.

This improvement is observed in the results, since the new path planner maximizes the area to be covered by the ASV in the monitoring task. A two-phase GA-based monitoring system is proposed in [3]. In the first phase of the system, the monitoring task aims to explore the water resource to locate contaminated areas. In the second phase, the vehicles are intended to exploit the contaminated areas identified during the exploration stage. In [30], the main objective is the patrolling of several WQP simultaneously. In order to solve the established problem, the authors propose an algorithm based on multi-objective GA, and more specifically the NSGA-II algorithm. This algorithm obtained good results in solving single-objective and multi-objective problems.

In [28], the patrolling of the Ypacarai lake is performed with a DRL-based system. In the system proposed by the authors, RGB images are used as the possible ASV positions and states, and the problem is modeled as a Markov Decision Problem (MDP). The authors trained a Deep Q-learning method based on convolutional neural networks using a customized reward function. The work was extended in [29]. The improved system uses a centralized approach strategy using multiple agents or ASVs. The advantage of using the centralized approach is that the system proposed by the authors has the ability to train the entire fleet of ASVs with only one neural network. The results obtained demonstrated the superiority of the centralized approach over the distributed Q-learning in the patrolling task. Another machine learning technique that is used as a basis is BO. In [18], the authors developed an Informative Path Planner (IPP) based on BO and Gaussian Process (GP) that aims to generate models of the WQP of the Ypacarai lake. To optimize the coordinates where the measurements should be taken, the authors propose different tailored acquisition functions. The work was extended to an improved monitoring system capable of solving multi-objective problems in [17]. The monitoring system proposed by the authors calculates the best positions to take measurements considering several WQP simultaneously. This problem is solved with acquisition functions, based on various multi-objective techniques, that fuse data from water quality sensors. This approach is extended in [19], where the problem is extended to multiple agents. A Multi-Objective approach is addressed by the same authors in [20], where paths are generated and optimized using Genetic Algorithms, considering a GP as base for the fitness function. The use of several ASVs allows speeding up the monitoring task by generating models of the WQP in less time.

Water resource monitoring problems with various agents or vehicles can also be solved by applying swarm intelligence algorithms. In [25], the authors developed a PSO and GP-based monitoring system, the Enhanced GP-based PSO. The system used measurements obtained from sensors in order to generate an accurate model of the WQP of the water resource and to detect peaks of water pollution. The difference between the actual models and the estimated models was very small. The Enhanced GP-based PSO was evaluated and compared with other PSO-based algorithms in [26] and [27]. In [26], the

focus of the evaluation was exploration, i.e., covering as much area as possible in order to minimize the error between the actual model and the estimated model of the entire water resource. The Enhanced GP-based PSO adjusted with the BO obtained the best response among the compared algorithms. In contrast, in [27], the focus was on exploiting areas with high pollution levels with the objective of detecting water resource pollution peaks. Among the compared algorithms, the one that obtained the best response was the Contamination algorithm, this algorithm is a variant of the Enhanced GP-based PSO. These evaluations were performed in uni-modal scenarios. Therefore, in [9], the work was extended by evaluating the algorithms in multi-modal scenarios. The results showed that the Enhanced GP-based PSO based on the Epsilon Greedy method obtained the best responses in detecting pollution peaks and obtaining an accurate model of the WQP of the water resource. Based on these results, the authors designed the AquaFeL-PSO monitoring system [8]. The AquaFeL-PSO is an enhancement of the Enhanced GP-based PSO that has two phases, the exploration phase and the exploitation phase. In the exploration phase, the ASVs traverse the entire surface of the water resource. At the end of the first phase, the system generates a first model of the WQP. The first model is used to divide the water resource into zones where the level of contamination is high, the action zones. Then, the ASVs are assigned to these zones, creating sub-populations of ASVs in order to perform the exploitation of the zones. The final model of the WQP is obtained by merging the models of the action zones with the first model generated. The Federated Learning (FL) technique is used in the exploitation phase. The FL allows each sub-population to act as a node or local server and adjust its own GP to generate a model of its action zone. The AquaFeL-PSO obtained the best answers in the evaluation of ground truths based on the Shekel function, the difference between the real models and the estimated models was minimal. At this point, it is evident that the AqualFel-PSO is one of the first methods that is evaluated with several benchmark functions instead of a based benchmark function. This performance evaluation represents a step towards the generalization of the proposed method towards a broader set of applications, such as different environments or measured data.

3 Statement of the problem

In this section the monitoring problem to be solved, as well as the considered assumptions of the monitoring system are presented.

3.1 Monitoring Problem

The water resource used as a scenario for the simulations is Lake Ypacarai, Fig. 1, located in Paraguay. This lake has two large inflows to the southeast and northwest, the Pirayú and Yukyry streams, respectively. In addition, it has small inflows distributed to the east and west of the lake. The only natural outlet of the lake is located to the north, the Salado River. The contamination of Lake Ypacarai has long been the case study of organizations and researchers in the country. The lake is polluted by sewage from surrounding houses and industries, and fertilizer residues from surrounding crops [13]. Because of this, periodic monitoring is carried out by different organizations and entities, in order to obtain the state of the water quality of Lake Ypacarai [5, 6]. These monitoring can be carried out with ASVs, reducing the time and by reaching remote locations inside the lake to take water measurements.

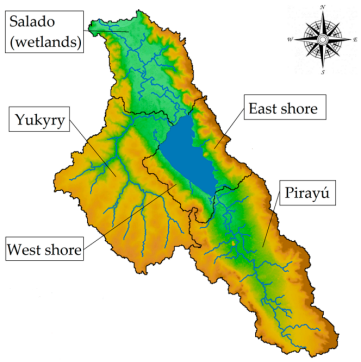


Fig. 1: Inflows and outflows of the Ypacarai lake [13]

The monitoring system consists of a fleet of ASVs composed of P vehicles. These vehicles have on-board sensors S to take water measurements. These measurements are used to generate an estimated model of the water resource $\hat{y}(\mathbf{x})$ and to calculate the speed $\mathbf{v}$ and position $\mathbf{x}$ of the ASVs. The measurements taken by the sensors are stored in a vector $\mathbf{s} = \{s_k \mid k = 1, 2, \ldots, n\}$, the term k refers to the number of measurements taken, and the coordinates where the measurements were taken are stored in the vector $\mathbf{q} = \{q_k \mid k = 1, 2, \ldots, n\}$. Measurements of the WQP are taken from a function that simulates the actual model of the WQP of the water resource $f(\mathbf{x})$. The actual model of the WQP is called the ground truth. That said, each measurement taken is represented as follows:

$$s_k = f(q_k) \tag{1}$$

The estimated model of the WQP of the water resource $\hat{y}(\mathbf{x})$ can be obtained by applying the regression model, Eq. 2 and taking a sufficient number of measurements k.

$$\hat{y}(\mathbf{x}) \approx f(\mathbf{x}) \tag{2}$$

3.2 Assumptions

In order to implement the monitoring system, the following assumptions have been considered:

- **Search space:** The search space is a matrix $\mathcal{M}$ with dimensions $m \times n$. Each element $\mathcal{M}_{i,j}$ has a state assigned to it: i) the value 0 represents the zones where the ASVs cannot travel, either because it is a forbidden zone, an obstacle, land, among others, and ii) the value 1 represents the available zones, that is, the zones where the ASVs can travel.
- **ASV:** The movements performed by the ASVs are considered ideal, there is no error in the trajectory. Collisions and obstacles are not considered. The autonomy of the vehicles allows to complete the monitoring task, each ASV travels 20km to complete the monitoring of the water resource.
- **Sensors:** The data provided by the sensors are free of error, including GPS data and data taken by the sensors of the WQP.
- **Communication:** The monitoring system has a global coordinator in the cloud. The ASVs communicate to the global coordinator via 4G or 5G technology. Communication between the sensors of the WQP and the ASV Guidance, Navigation and Control (GNC) system is via Universal Serial Bus (USB). Fig. 2 shows the communication of the monitoring system based on the centralized learning technique.

4 PSO-based path planning algorithms

This section explains the path planners that are used as the basis for the AquaFeL-PSO. In addition, the operation of the AquaFeL-PSO monitoring system is explained.

4.1 Classic Particle Swarm Optimization (PSO)

PSO is a heuristic optimization algorithm developed by [10] using as inspiration the social behavior of a flock of birds. This optimization algorithm is

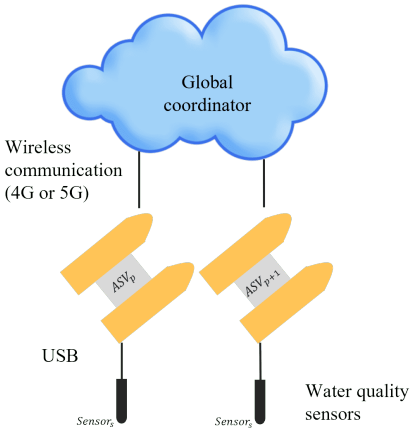


Fig. 2: Communication system based on centralized learning technology

composed of particles p that represent possible solutions to an optimization problem, the term swarm is used to refer to a set of particles. To obtain the best solution, the particles use their own experience and the experience of the other particles in the swarm. Therefore, the particles are connected, constantly sharing information as they move in a multidimensional space. The calculation of particle motion is based on: i) a control parameter, ii) a self-cognitive component, and iii) a social component. The auto-cognitive component **pbest** is based on the own experience of the particle and represents the best solution of the particle up to the current time. However, the social component **gbest** is based on the experience of the swarm and is the best solution found by all particles in the swarm up to the current time. The particles p have a velocity $\mathbf{v}_p$ and a position $\mathbf{x}_p$. To calculate these parameters, the following equations are applied:

$$\mathbf{v}_p^{t+1} = w\mathbf{v}_p^t + c_1 r_1^t \left[\mathbf{pbest}_p^t - \mathbf{x}_p^t\right] + c_2 r_2^t \left[\mathbf{gbest}^t - \mathbf{x}_p^t\right] \tag{3a}$$

$$\mathbf{x}_p^{t+1} = \mathbf{x}_p^t + \mathbf{v}_p^{t+1} \tag{3b}$$

the terms $\mathbf{v}_p^{t+1}$ and $\mathbf{x}_p^{t+1}$ are the values of the next velocity and next position of the particle p, respectively. The control parameter is composed of the inertia weight w and the velocity $\mathbf{v}_p^t$ of the particle p at time t. The c_1 and c_2 terms are acceleration coefficients that determine the importance of the self-cognitive and social components. In other words, they determine the weights of the exploitation approach, approach that allows to achieve the self-component or local best, and of exploration, approach that is achieved with the social component or also called global best. The terms r_1 and r_2 are random values that vary in the range of 0 and 1.

4.2 Enhanced GP-based PSO

In this subsection, the surrogate model used, the GP, is explained, since the GP responses are used in the equations of motion of the Enhanced GP-based PSO. Then, the operation of the path planner itself is explained. Finally, the variants of the algorithm used in the AquaFeL-PSO comparison are explained.

4.2.1 Gaussian Process Regression (GPR)

Gaussian Process (GP) modelling is a machine learning technique based on Bayesian inference [22]. The behavior of the GP is mainly determined by two components: the covariance function or kernel function, and the mean function [22]. Normally, the mean function is set to 0, so the GP would depend only on the kernel function. The purpose of the kernel function is to determine the shape, variability and smoothness of the model of the WQP of the water resource. The Enhanced GP-based PSO monitoring system uses the kernel function called Radial Basis Function (RBF), since, according to [17], this kernel function has the best behavior for water resources.

The GPR is updated using the input data, which is a set D. These input data are treated as random variables and, then conditioned and marginalized to fit the kernel function and measured values. In response to the equations shown in Eq. 4, the mean value $\mu(\mathbf{x}_*)$ and standard deviation $\sigma(\mathbf{x}_*)$ of the GPR $\hat{f}(\mathbf{x})_*$ are obtained.

$$\mu_{\hat{f}(\mathbf{x}_i)_*|D} = K_*^T K^{-1} f(\mathbf{x}) \tag{4a}$$

$$\sigma_{\hat{f}(\mathbf{x}_i)_*|D} = K_{**} - K_*^T K^{-1} K_* \tag{4b}$$

From the fitted kernel, the data of K, K_{**} and K_* are obtained. These data comprise covariances between known data $k(\mathbf{x}, \mathbf{x})$, unknown data $k(\mathbf{x}*, \mathbf{x}*)$, and covariances between both the known and unknown data $k(\mathbf{x}, \mathbf{x}*)$.

$$K = \begin{bmatrix} K & K_* \\ K_*^T & K_{**} \end{bmatrix} = \begin{bmatrix} k(\mathbf{x}, \mathbf{x}) & k(\mathbf{x}, \mathbf{x}*) \\ k(\mathbf{x}*, \mathbf{x}) & k(\mathbf{x}*, \mathbf{x}*) \end{bmatrix} \tag{5}$$

The obtained data D along with the kernel are used to update the hyperparmeters of the kernel itself, which, in this case, corresponds to hyperparameter ℓ of the RBF kernel. We denote that a GP "converges" when a value for ℓ larger than a certain value can be obtained.

4.2.2 Path Planner

The Enhanced GP-based PSO monitoring system combines the PSO components, the local best **pbest** and the global best **gbest**, with the GP, the mean of the model μ and the standard deviation σ. In this monitoring system, the ASVs are the particles and the swarm is represented by the fleet of ASVs. The data obtained from the GP allows the monitoring system to be guided by the estimated model data of the WQP. With this data, the ASVs can travel to unexplored areas, regions where the standard deviation or so-called uncertainty is high, and characterize in depth areas where contamination is high, i.e. zones where the mean of the model is high.

The Enhanced GP based PSO takes measurements of the water resource in order to update the GP and obtain an estimated model of the WQP. With the model data, the velocity and position of the ASVs are calculated by applying Eq. 6a and Eq. 6b respectively.

$$\begin{aligned}\mathbf{v}_p^{t+1} = w\mathbf{v}_p^t + c_1 r_1^t[\mathbf{pbest}_p^t - \mathbf{x}_p^t] + c_2 r_2^t[\mathbf{gbest}^t - \mathbf{x}_p^t] \\ + c_3 r_3^t[\mathbf{max\_un}^t - \mathbf{x}_p^t] + c_4 r_4^t[\mathbf{max\_con}^t - \mathbf{x}_p^t]\end{aligned} \tag{6a}$$

$$\mathbf{x}_p^{t+1} = \mathbf{x}_p^t + \mathbf{v}_p^{t+1} \tag{6b}$$

As in the Classic PSO, to calculate the next velocity $\mathbf{v}_p^{t+1}$ of the particle p, Eq. 6a uses the control parameter data $w\mathbf{v}_p^t$, the local best $\mathbf{pbest}_p^t$ and the global best $\mathbf{gbest}^t$. However, two new terms are added, the $\mathbf{max\_un}^t$ and $\mathbf{max\_con}^t$. The $\mathbf{max\_un}^t$ represents the coordinate where the maximum value of the model uncertainty max_σ is found at time t. The $\mathbf{max\_con}^t$ term refers to the coordinate where the maximum value of the model mean max_μ or the maximum contamination of the water resource is found at time t. The constants c_3 and c_4 are acceleration constants that determine the importance of exploration (**max_un**) and exploitation (**max_con**). r_3 and r_4 are random values between [0, 1]. To calculate the next position $\mathbf{x}_p^{t+1}$ of the particle p, the same equation of the Classical PSO is used. This equation is shown in Eq. 6b.

Water measurements are taken every l distance traveled by the ASVs. This condition is applied in order to reduce the GP processing time, since the greater the number of measurements, the longer the processing time. Additionally, the kernel provides high covariance values for coordinates that are close. Therefore, it is not necessary to perform measurements that are very close to each other. To obtain the value of l, Eq. 7 is applied [17].

$$l = \lambda \times \ell^t \tag{7}$$

where λ represents a proportion value and ℓ^t refers to the length scale of the GP at time t.

4.2.3 Variants of the Enhanced GP-based PSO

Two variants of the Enhanced GP-based PSO are shown below. These variants are based on keeping two active terms in Eq. 6a, the control parameter and one of the PSO components or GP responses. The purpose of these variants is to observe the behavior of the terms that are kept active to obtain the model of the WQP of the water resource and to detect pollution peaks.

- **Uncertainty:** In this variant, the term that remains active along with the control parameter $w\mathbf{v}$ is the coordinate of the maximum uncertainty **max_un**. This variant allows the ASVs to target unexplored areas of the water resource surface because the **max_un** term is obtained from the model uncertainty. The velocity of the ASVs are updated according to the following equation:

$$\mathbf{v}_p^{t+1} = w\mathbf{v}_p^t + c_3 r_3^t[\mathbf{max\_un}^t - \mathbf{x}_p^t] \tag{8}$$

- **Contamination:** This variant allows the ASVs to target the areas where they detect the highest level of contamination. This is due to the terms that remain active, the control parameter $w\mathbf{v}$ and the coordinate of the maximum contamination **max_con**. The last term refers to the mean of the GP model. Eq. 9 is used to update the velocity of the ASVs.

$$\mathbf{v}_p^{t+1} = w\mathbf{v}_p^t + c_4 r_4^t[\mathbf{max\_con}^t - \mathbf{x}_p^t] \tag{9}$$

  The position of the ASVs in both variants is updated according to Eq. 6b.

4.3 AquaFeL-PSO

The AquaFeL-PSO is a monitoring system developed in [8]. This system is based on the PSO, GP and FL paradigm. The AquaFeL-PSO is an improvement of the Enhanced GP-based PSO, the system consists of splitting the monitoring task into two different approaches in two different periods. When starting the monitoring task, the algorithm focuses on covering the largest possible surface of the water resource in order to have a first model of the WQP of the water body, this phase is called exploration phase. After the ASVs have covered a certain distance, the focus shifts to the exploitation of areas with high levels of contamination in order to characterize in depth the WQP, this phase is called the exploitation phase.

4.3.1 Exploration phase

The main objective of the exploration phase is to obtain a first model of the WQP of the water resource in order to determine the areas where contamination levels are severe so that the WQP can be more accurately characterized. To meet this objective, the ASVs must travel over a large part of the surface of the water body, therefore, the velocity equation in this phase is Eq. 10, equation obtained with the results of [26]. The results obtained in [26] demonstrate that for the exploration approach, the terms that should remain active are the best local **pbest** and the coordinate of maximum uncertainty **max_un**, in addition to the control parameter $w\mathbf{v}$. With this equation of motion, the monitoring system succeeds in generating a first reliable model.

$$\mathbf{v}_p^{t+1} = w\mathbf{v}_p^t + c_1 r_1^t[\mathbf{pbest}_p^t - \mathbf{x}_p^t + c_3 r_3^t[\mathbf{max\_un}^t - \mathbf{x}_p^t] \tag{10}$$

4.3.2 Exploitation phase

The exploitation phase has several stages: the division of the contaminated areas into action zones, the assignment of the ASVs to the action zones found, the exploitation of the action zones and the obtaining of the final model of the WQP of the water resource by applying the FL concept.

4.3.2.1 Action zones

The action zones are areas where the level of contamination of the water resource is considered worrisome or alarming. The level of contamination is considered worrisome when the percentage of contamination is between 33% and 65% of the maximum contamination value found in the exploration phase, and is considered alarming when the value equals or exceeds 66% of the maximum contamination value. The acceptable level is a value lower than 33%. An example of contamination levels is shown in Fig. 3.

The action zones are circles drawn from a center and a radius *rad*. The center of the action zone are the coordinates where the maximum contamination values are found and the radius of the action zone is determined according to the number of ASVs in the fleet n_{ASV} and the width of the water resource *length*, Eq. 11. To obtain the different action zones, first the coordinate of the maximum contamination value is found and with the radius calculated using Eq. 11, the area covered by the action zone is plotted. To obtain the next action zone, the coordinates belonging to the previously determined action zones are no longer considered in the following action zones, i.e. a point (x, y) in the search space only belongs to one action zone. Because of this, there is no overlapping of action zones.

$$rad = length/n_{ASV} \tag{11}$$

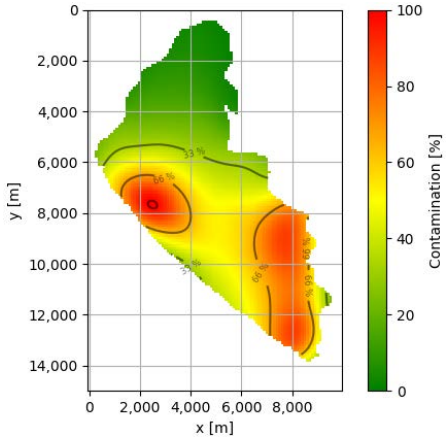


Fig. 3: Example of water contamination levels of the water resource

Regarding the number of action zones, two cases are considered: i) the number of action zones is less than the number of ASVs in the fleet, ii) the number of action zones is equal to the number of ASVs in the fleet. The AquaFeL-PSO does not consider the case where the number of action zones is greater than the number of ASVs in the fleet. To solve the latter case, more ASVs would be needed.

4.3.2.2 Resource allocation

ASVs are assigned according to the distance between the vehicle and the action zone. The ASV that is closest to a given action zone is the vehicle that has the task of exploiting that area. In case the number of ASVs is greater than the number of action zones, more vehicles are assigned to the action zones with higher priority. The priority of the action zone is determined by considering the peak value of the zone, from the data obtained in the exploration phase, the peak with the highest contamination value is the one with the highest priority max_prt. Eq. 12 is applied to calculate the highest priority.

$$max\_prt = n_{ASV} * 10 + 10 \tag{12}$$

The maximum value of the priority is determined by the total number of ASVs n_{ASV}, since it may be the case that the number of action zones is equal to the number of vehicles. Each time a priority value is assigned to an action zone, the priority value for the next zone decreases by 10 points.

4.3.2.3 Exploitation of the action zones

The exploitation task is performed after assigning the ASVs to the action zones. Since the vehicles must exploit different action zones, the fleet is divided into sub-populations. This allows information to be shared only between the ASVs that are assigned to the same action zone, not interfering in the exploitation of the other areas. Each sub-population generates a model of the WQP with the data from the first model obtained in the exploration phase together with the measurements taken by the vehicles in their assigned area. To calculate the velocity of the ASVs in this phase, Eq. 13 is applied. This equation is the result obtained in [27], where the focus of the monitoring task was the characterization of WQP (exploitation).

$$\mathbf{v}_p^{t+1} = w\mathbf{v}_p^t + c_1 r_1^t[\mathbf{pbest}_p^t - \mathbf{x}_p^t] + c_2 r_2^t[\mathbf{gbest}^t - \mathbf{x}_p^t] + c_4 r_4^t[\mathbf{max\_con}^t - \mathbf{x}_p^t] \tag{13}$$

To obtain the global best **gbest** and the coordinate of the maximum contamination value **max_con** terms, only the data from the ASVs of the sub-population and the model of the WQP generated with the data from that sub-population are considered.

4.3.2.4 Federated Learning

The final model of the WQP of the water resource is obtained by applying the Federated Learning (FL) concept, a technique developed by McMahan et al. [15, 14, 12, 11]. This concept was introduced with the aim of updating language models in cell phones. Through FL, an ensemble ML model is obtained [31]. To generate this model, data found in multiple sites is used. The data is trained at the same site, using local servers, which then send only the final training result to the central server. According to [31], the final results of the models generated with the FL and with the centralized learning technique are quite similar. The FL preserves the security and privacy of the data and nodes respectively, moreover, it allows to generate better results, since the ML models are trained collaboratively [31, 4]. This last point can be observed in the proposed monitoring system.

Reference is made to the information provided by [31] to explain the mathematical definition of the FL. The node vector $\mathbf{F} = \{\mathcal{F}_k \mid k = 1, 2, \ldots, \mathcal{L}\}$ is considered, where $\mathcal{L}$ are the nodes and k is the node number. For this monitoring system, the sub-populations are considered the nodes in the FL technique. To train the ML models on the nodes, their own data are used $\mathbf{W} = \{\mathcal{D}_k \mid k = 1, 2, \ldots, \mathcal{L}\}$. These data refers to the water measurements and the coordinates where the measurements were taken. In case of having a central server, centralized learning technique, the data of the nodes $\mathcal{D} = \mathcal{D}_1 \cup \mathcal{D}_2 \cup ... \cup \mathcal{D}_\mathcal{L}$ are merged to generate a model $\mathcal{M}_{CEN}$. In contrast, with the FL technique, models $\mathcal{M}_{FED}$ are generated at each node, since each node trains its own ML model with its own data. Furthermore, the accuracy

$\mathcal{V}_{FED}$ of the model generated with the FL technique $\mathcal{M}_{FED}$ is very similar to the accuracy $\mathcal{V}_{CEN}$ of the model generated with the centralized learning technique $\mathcal{M}_{CEN}$. δ being a non-negative real number in Eq. 14, the FL algorithm loses an accuracy of δ.

$$|\mathcal{V}_{FED} - \mathcal{V}_{CEN}| < \delta \tag{14}$$

The FL technique is used in the AquaFeL-PSO in order to generate models of the WQP of the action zones in the sub-populations, the sub-populations are the nodes in the FL. At the end of the monitoring task, merging the first model of the WQP obtained in the exploration phase with the models of the WQP generated in the sub-populations. The generation of the final model of the WQP and the operation of the FL technique works as follows in the AquaFeL-PSO:

1. A first model of the WQP is generated at the end of the exploration phase on the central server, joining all the measurements taken by the ASVs of the fleet.
2. In the exploitation phase, after assigning the vehicles to the action zones, each sub population is a node, where the model of the WQP of the action zone is generated by merging the data from the exploration phase with the measurements taken by the sub population. This allows to have a more accurate model of the action zone.
3. To obtain the final model of the WQP, the first model obtained in the exploration phase is used as a base, and the mean values of the coordinates are replaced with the values of the mean of the coordinates obtained in the exploration phase, and the values of the first model in the coordinates of the action zones are replaced by the values of the models generated in the sub-populations of the corresponding action zones. An example schematic of the operation is shown in Fig. 4.

To obtain the final model of the WQP of the water resource, the following cases are considered:

- **Case 1:** The GP converges in the exploration phase and in the exploitation phase. That is, it was possible to generate a first model in the exploration phase, and, in the exploitation phase, more accurate models of the action zones were generated. Therefore, to obtain the final model of the WQP, the data from the models of all the action zones are replaced in the first model.
- **Case 2:** The GP converges in the exploration phase. However, in the exploitation phase, the GP does not converge in all nodes or sub-populations. In this case, the model data of the WQP from the action zones where the GP converged are replaced in the first model, and for the action zones where the GP did not converge, the data from the first model are used.
- **Case 3:** The GP converges in the exploration phase. However, the GP does not converge in the exploitation phase, in any action zone, it is not

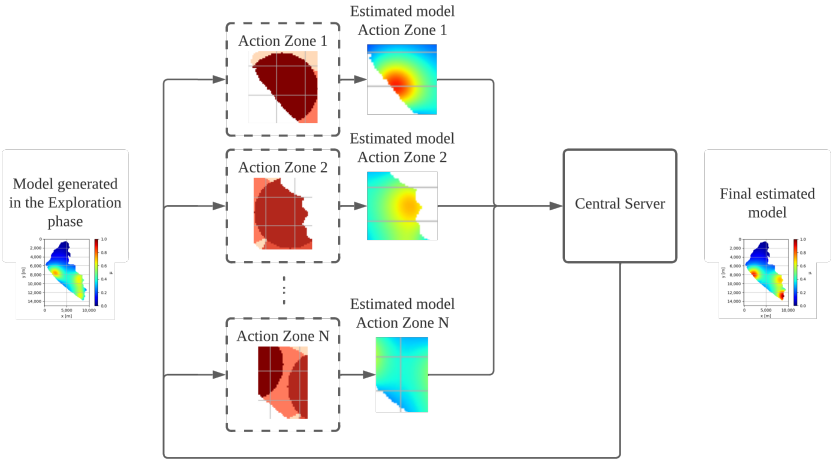


Fig. 4: Final model of the WQP generation process using Federated Learning technique

possible to obtain a more accurate model of these action zones. In this case, the final model is equal to the first model, which was obtained in the exploration phase.

- **Case 4:** Finally, the GP does not converge in the exploration phase. In this case it is considered that the monitoring system was not successful in generating the model of the WQP of the water resource.

The monitoring system is considered successful in Cases 1, 2 and 3.

5 Results and discussion

This section presents the results obtained from the evaluation of the AquaFeL-PSO[1] in different contamination profiles and the comparison with the performance of the Enhanced GP-based PSO variants. The contamination profiles on which the algorithms are evaluated are listed, as well as the performance metrics and parameter and hyper-parameter settings.

[1] https://github.com/MicaelaTenKathen/AquaFeL_bench.git (accessed on 02 December 2022)

The monitoring systems were developed in Python using the following libraries: Scikit-learn[2], DEAP[3] and Bayesian Optimization[4]. A laptop computer with 8GB RAM and an Intel i5 1.60 GHz processor was used to run the simulations.

5.1 Ground truth

The proposed scenario for the simulations is the Ypacarai lake. Since the objective is to evaluate the performance of the AquaFeL-PSO in different contamination profiles, several benchmark functions are used. Each benchmark function is a contamination profile. These functions have the characteristics of being multidimensional, multimodal, continuous, and deterministic. The benchmark functions and their equations are listed in the Table 1.

A ground truth generated from the different benchmark functions can be seen in Fig. 5. Scenarios where the contamination is dispersed throughout the lake are considered, such as in Fig 5b and Fig. 5j. In addition, extreme scenarios are also considered, where the contamination is extremely severe and varies abruptly over a small surface area, as in Fig. 5a and Fig. 5f. For each benchmark function, 10 different ground truth models are used.

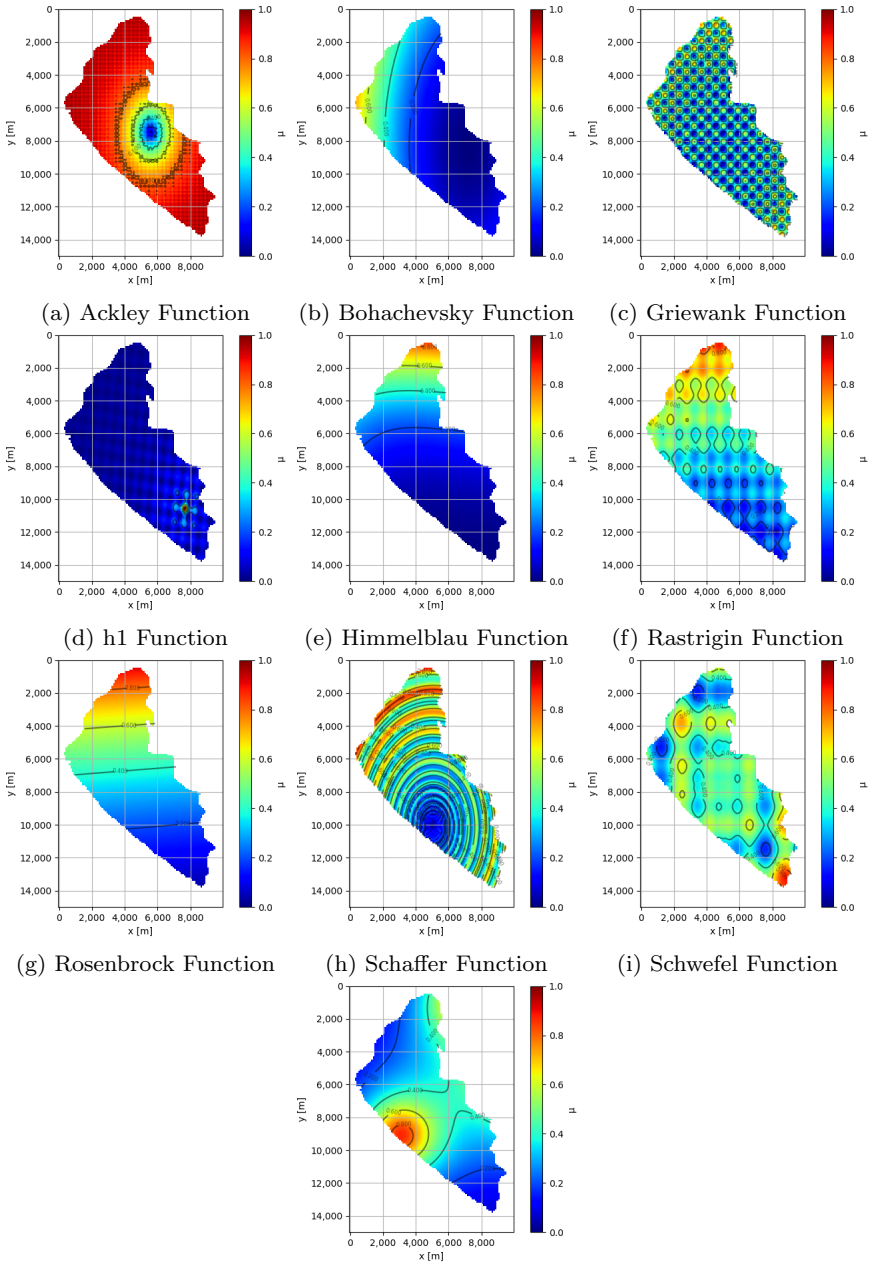
[2] https://scikit-learn.org/stable/ (accessed on 27 November 2022)

[3] https://deap.readthedocs.io/en/master/ (accessed on 27 November 2022)

[4] https://github.com/fmfn/BayesianOptimization (accessed on 27 November 2022)

Table 1: Benchmark functions used as contamination profiles

Benchmark f.	Equation		Example
Ackley	$f(\mathbf{x}) = 20 - 20\exp\left(-0.2\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}\right) + e - \exp\left(\frac{1}{N}\sum_{i=1}^{N}\cos(2\pi x_i)\right)$	(15)	Fig. 5a
Bohachevsky	$f(\mathbf{x}) = \sum_{i=1}^{N-1}(x_i^2 + 2x_{i+1}^2 - 0.3\cos(3\pi x_i) - 0.4\cos(4\pi x_{i+1}) + 0.7)$	(16)	Fig. 5b
Griewank	$f(\mathbf{x}) = \frac{1}{4000}\sum_{i=1}^{N} x_i^2 - \prod_{i=1}^{N}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	(17)	Fig. 5c
h1	$f(\mathbf{x}) = \frac{\sin(x_1 - \frac{x_2}{8})^2 + \sin(x_2 + \frac{x_1}{8})^2}{\sqrt{(x_1 - 8.6998)^2 + (x_2 - 6.7665)^2} + 1}$	(18)	Fig. 5d
Himmelblau	$f(x_1, x_2) = (x_1^2 + x_2 - 11)^2 + (x_1 + x_2^2 - 7)^2$	(19)	Fig. 5e
Rastrigin	$f(\mathbf{x}) = 10N + \sum_{i=1}^{N} x_i^2 - 10\cos(2\pi x_i)$	(20)	Fig. 5f
Rosenbrock	$f(\mathbf{x}) = \sum_{i=1}^{N-1}(1 - x_i)^2 + 100(x_{i+1} - x_i^2)^2$	(21)	Fig. 5g
Schaffer	$f(\mathbf{x}) = \sum_{i=1}^{N-1}(x_i^2 + x_{i+1}^2)^{0.25} \cdot \left[\sin^2(50 \cdot (x_i^2 + x_{i+1}^2)^{0.10}) + 1.0\right]$	(22)	Fig. 5h
Schwefel	$f(\mathbf{x}) = 418.9828872724339 \cdot N - \sum_{i=1}^{N} x_i \sin\left(\sqrt{\lvert x_i\rvert}\right)$	(23)	Fig. 5i
Shekel	$f_{\text{Shekel}}(\mathbf{x}) = \sum_{i=1}^{M}\frac{1}{c_i + \sum_{j=1}^{N}(x_j - a_{ij})^2}$	(24)	Fig. 5j



(a) Ackley Function (b) Bohachevsky Function (c) Griewank Function

(d) h1 Function (e) Himmelblau Function (f) Rastrigin Function

(g) Rosenbrock Function (h) Schaffer Function (i) Schwefel Function

(j) Shekel Function

Fig. 5: Examples of ground truth with different benchmark functions

Due to the fact that the range of the WQP values varies randomly in the ground truths, all ground truths used are normalized using the Eq. 25 in order to make comparisons of algorithm performance.

$$f_{\text{Normalized}}(\mathbf{x}) = \frac{f_{\text{Benchmark}}(\mathbf{x}) - f_{\text{min\_Benchmark}}(\mathbf{x})}{f_{\text{max\_Benchmark}}(\mathbf{x}) - f_{\text{min\_Benchmark}}(\mathbf{x})} \tag{25}$$

the current value of the benchmark function is represented by the term $f_{Benchmark}(\mathbf{x})$, the term $f_{min\_Benchmark}(\mathbf{x})$ represents the minimum value of the benchmark function, and the term $f_{max\_Benchmark}(\mathbf{x})$ refers to the maximum value of the benchmark function.

5.2 Performance metric

The performance of the algorithms are evaluated according to: i) success rate of the algorithms, ii) model of the WQP generated from the action zones, iii) detection of the peaks of the action zones, and iv) model of the WQP generated from the whole water resource surface. The success rate of the algorithms corresponds to the percentage of cases where the monitoring system succeeded in generating models of the WQP of the water resource. It is considered a success when the monitoring system was able to generate a model of the WQP, i.e., when the GP converged. In the case of the AquaFeL-PSO, Cases 1, 2 and 3 mentioned in Section 4.3.2.4 are considered successful.

To evaluate the reliability of the generated models of the WQP, the Mean Square Error (MSE) and the error between the ground truth and model data generated by the monitoring system are calculated. In order to evaluate the models obtained from the action zones, the MSE is calculated between the data found in the coordinates of the ground truth action zones $f(\mathbf{x})$ and the generated model y, Eq. 26.

$$\text{MSE}_{action\_zone}(f(\mathbf{x}), y) = \frac{1}{n_{action\_zone}} \sum_{k=0}^{n_{action\_zone}-1} (f(\mathbf{x}_k) - y_k)^2 \tag{26}$$

The same procedure is carried out to obtain the results corresponding to the model of the WQP of the entire surface of the lake, with the difference that all the coordinates of the search space of the water resource are considered. The equation used to calculate the MSE value is Eq. 27.

$$\text{MSE}_{map}(f(\mathbf{x}), y) = \frac{1}{n_{map\_points}} \sum_{k=0}^{n_{map\_points}-1} (f(\mathbf{x}_k) - y_k)^2 \tag{27}$$

Finally, in order to know the capacity of the algorithms to detect the peaks of the action zones, the error between the peaks of the ground truth

$f(\mathbf{x}_{action\_zone\_peak})$ and the peaks of the generated model $y_{action\_zone\_peak}$ is calculated using Eq. 28.

$$\text{Error}_{action\_zone\_peak}(f(\mathbf{x}), y) = |f(\mathbf{x}_{action\_zone\_peak}) - y_{action\_zone\_peak}| \quad (28)$$

5.3 Setting Simulation Parameters

The ASV fleet has four vehicles that can travel at a maximum speed of 2 m/s. The maximum distance that ASVs can travel is 20km. Once the ASVs reach this distance, the monitoring task is considered to be complete. Regarding the GP configuration, the initial value of the length scale used is 10% of the size of the surface area of the water resource [18], therefore the length scale is equal to 10. The length scale values are in the range $[0.1, 10^5]$. To determine the λ value, [17] and [25] are used as a basis. In order to balance the run time of the monitoring system and the number of measurements, the λ value is set to 0.3. Since the AquaFeL-PSO is composed of two phase, the exploration focus phase and the exploitation focus phase, the acceleration coefficient values vary. Table 2 shows the values for the two phases. The values for the exploration phase were obtained from [26] and for the exploitation phase the values obtained from [27] were considered.

Table 2: Values of the acceleration coefficients for the phases of the AquaFeL-PSO

Hyper-parameter	Exploration phase	Exploitation phase
c_1	2.0187	3.6845
c_2	0	1.5614
c_3	3.2697	0
c_4	0	3.1262

Another variable that must be established is the distance that the ASVs must travel in the exploration phase and in the exploitation phase. To set this value, the results obtained in [8] are considered. Therefore, the ASVs travel 10km in the exploration phase and then travel 10km exploiting the most contaminated areas (action zones).

5.4 Performance Comparison

After setting the parameters for the AquaFeL-PSO, comparisons are made with two variant algorithms of the Enhanced GP-based PSO, the Uncertainty algorithm and the Contamination algorithm. The performance of AquaFeL-PSO is compared with these algorithms because the Uncertainty algorithm allows to cover the largest area of the water resource, since it focuses on exploration, and the Contamination algorithm focuses on characterizing the WQP of the most contaminated areas since its main focus is exploitation. Considering Eq. 8, the values for the acceleration coefficients of the Uncertainty algorithm are equal to: $c_1 = 0, c_2 = 0, c_3 = 3$, and $c_4 = 0$, and considering Eq. 9, the coefficients of the Contamination algorithm are set as follows: $c_1 = 0, c_2 = 0, c_3 = 0$, and $c_4 = 3$. These values were established considering [25], [26] and [27]. One consideration taken is that in all simulations, with the three algorithms, the ASVs started from the same initial position.

Table 3 shows the success rate of the algorithms with the different benchmark functions. For the success cases, Cases 1, 2 and 3 of Section 4.3.2.4 are considered. The results where the success rate is 0 is because Case 4 of the aforementioned section is presented. It is considered a success when the GP converged and it was possible to generate a model of the WQP of the water resource. The algorithm that was able to generate water resource quality models in more benchmark functions was the AquaFeL-PSO. This is due to the two functions that the algorithm has, since first its objective is to cover the entire surface of the lake, which allows the system to generate a first model of the WQP. Then, when it switches to the exploitation phase, more accurate models of the action zones are generated. This allows for higher success rates because the cases mentioned in Section 4.3.2.4 are retained. However, there are cases where the GP does not converge and is not able to generate a model of the WQP in the exploration phase, as was the case in the Griewank and Schaffer functions. The reason why the GP did not converge is the value of the length scale. The minimum value set for the GP was 0.1. However, there are functions where the ground truth values vary so sharply between neighboring coordinates that the minimum value set was high for the length scale of the GP.

In the generation of the action zone models, as shown in Table 4, there are cases where the three algorithms have a success rate of 100%, the monitoring system that generates the most reliable models, by a small difference, is the Contamination algorithm. This is because in this algorithm, the ASVs go directly to the areas of highest contamination, which would be the action zones. However, this algorithm is not able to generate any model in at least 4 benchmark functions and in two functions, the rates vary between 10% to 60%. On the other hand, the AquaFeL-PSO is able to generate models for 8 of the 10 benchmark functions, of which 3 of the functions, the success rate varies between 20% and 50%.

Table 3: Success rate of the compared algorithms

Benchmark Function	Uncertainty Algorithm (%)	Contamination Algorithm (%)	AquaFeL-PSO (%)
Ackley	0	0	50
Bohachevsky	100	100	100
Griewank	0	0	0
h1	0	0	20
Himmelblau	100	100	100
Rastrigin	0	10	50
Rosenbrock	100	100	100
Schaffer	0	0	0
Schwefel	10	60	100
Shekel	100	100	100

Table 4: MSE of the model of the action zones of the compared algorithms

Benchmark Function	Uncertainty Algorithm	Contamination Algorithm	AquaFeL-PSO
Ackley	-	-	**0.09758 ± 0.14598**
Bohachevsky	0.01355 ± 0.03104	**0.01278 ± 0.02958**	0.01343 ± 0.03301
Griewank	-	-	-
h1	-	-	**0.07705 ± 0.00496**
Himmelblau	0.03224 ± 0.08064	**0.03182 ± 0.08195**	0.03238 ± 0.08298
Rastrigin	-	0.10513 ± 0.21185	**0.09066 ± 0.17625**
Rosenbrock	0.03940 ± 0.06415	0.04055 ± 0.06713	**0.03868 ± 0.06604**
Schaffer	-	-	-
Schwefel	0.07580 ± 0.10647	0.05614 ± 0.09920	**0.05434 ± 0.11330**
Shekel	0.03420 ± 0.08262	**0.03388 ± 0.08469**	0.03419 ± 0.08051

Despite generating the most reliable models of the action zones, the Contamination algorithm did not obtain the best results in detecting contamination peaks, Table 5. The algorithm that performed the best in detecting action zone contamination peaks was AquaFeL-PSO. This is due to the fact that, as Uncertainty focuses on exploring, it does not take into account the pollution peaks and therefore does not characterize in depth the WQP in these zones. However, the Contamination algorithm does have the ability to characterize the parameters but, since it does not have the ability to explore the lake surface, it does not detect the peaks of the action zones because they are stuck at a local maximum. In contrast, the AquaFeL-PSO combines both approaches, allowing it to cover a large part of the lake surface and then detect contamination peaks in polluted areas.

The monitoring system that generates the best models of lake WQP is the AquaFeL-PSO. The results can be seen in Table 6. In most of the contamination profiles, except for the ground truths of the Griewank and Schaffer

Table 5: Error in the peaks of the action zones of the compared algorithms

Benchmark Function	Uncertainty Algorithm	Contamination Algorithm	AquaFeL-PSO
Ackley	-	-	**0.41941 ± 0.54160**
Bohachevsky	0.05470 ± 0.04451	0.03746 ± 0.11310	**0.02621 ± 0.08778**
Griewank	-	-	-
h1	-	-	**0.73664 ± 0.65926**
Himmelblau	0.07676 ± 0.17413	0.02539 ± 0.07548	**0.01744 ± 0.04327**
Rastrigin	-	**0.21511 ± 0.47034**	0.32011 ± 0.56378
Rosenbrock	0.05557 ± 0.15710	0.02898 ± 0.04707	**0.01409 ± 0.02622**
Schaffer	-	-	-
Schwefel	0.42700 ± 0.72971	0.30488 ± 0.59490	**0.29774 ± 0.57475**
Shekel	0.03262 ± 0.10427	0.05142 ± 0.17252	**0.01799 ± 0.10266**

functions, the best performance was obtained with the AquaFeL-PSO. In the Rastrigin function, it can be seen that the Contamination algorithm is lower than the value of the AquaFeL-PSO. However, the success rate of the Contamination algorithm was only 10%, i.e., it obtained only one model of the WQP out of 10 monitoring task simulations.

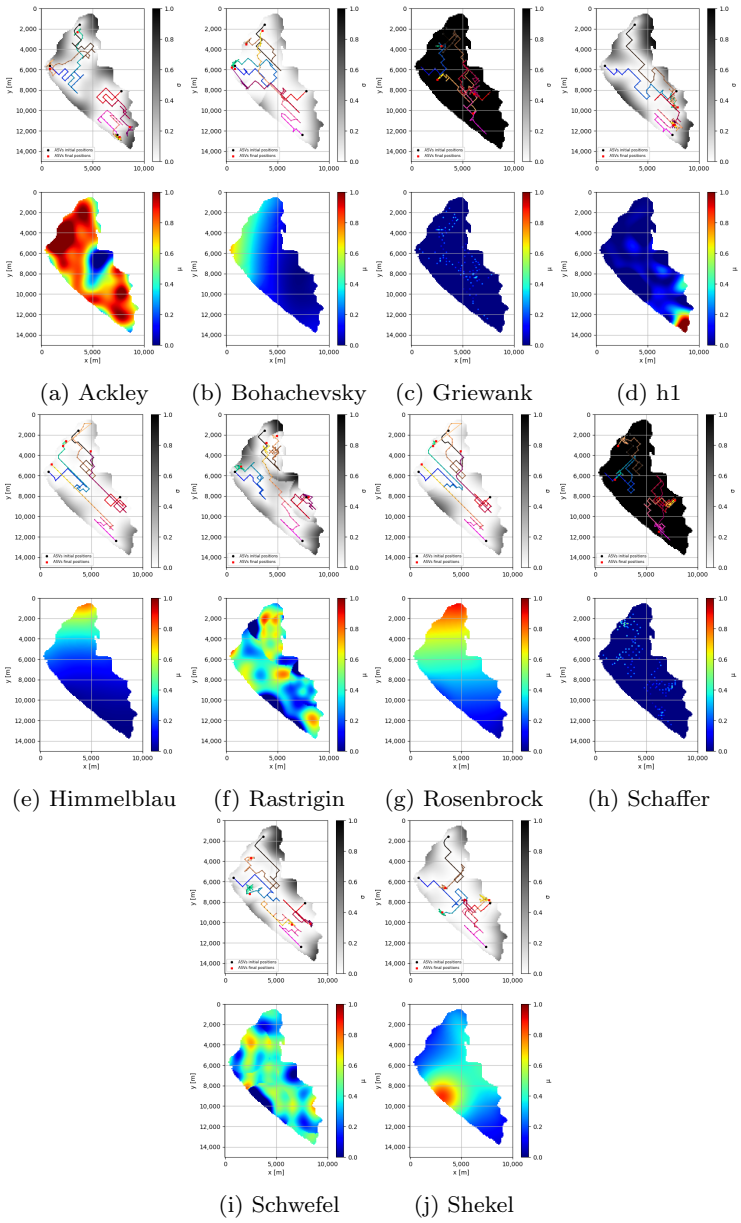
Table 6: MSE of the model of the Ypacarai Lake of the compared algorithms

Benchmark Function	Uncertainty Algorithm	Contamination Algorithm	AquaFeL-PSO
Ackley	-	-	**0.13269 ± 0.11981**
Bohachevsky	0.00064 ± 0.00060	0.00097 ± 0.00133	**0.00045 ± 0.00083**
Griewank	-	-	-
h1	-	-	**0.10568 ± 0.07438**
Himmelblau	0.00108 ± 0.00142	0.00030 ± 0.00024	**0.00011 ± 0.00023**
Rastrigin	-	**0.03636***	0.06249 ± 0.06181
Rosenbrock	0.00108 ± 0.00075	0.00041 ± 0.00059	**0.00008 ± 0.00011**
Schaffer	-	-	-
Schwefel	0.05992*	0.07196 ± 0.06012	**0.04742 ± 0.07190**
Shekel	0.00056 ± 0.00114	0.00128 ± 0.00155	**0.00042 ± 0.00136**

*The mean value is the MSE of the only scenario that the algorithm was able to generate a model of the WQP of the water resource.

The figures in Fig. 6 show the results obtained with the AquaFeL-PSO in different contamination profiles. The maps at the top represent the uncertainty of the model during the monitoring task. In addition, the movement of the ASVs is represented by colored lines on the top map, the initial positions are indicated by black dots and the final positions are represented by

red dots. The maps shown at the bottom represent the models of the WQP. Fig. 6a and Fig. 6d show the results obtained with the Ackley function and h1 function as ground truth, respectively. In these examples, it was possible to generate models with the AquaFeL-PSO in the exploration phase, so that first models were obtained. However, due to the value of the length scale of the GP, the GP did not converge and it was not able to generate models of the action zones in the exploitation phase. Because of this, the final results were the models obtained in the exploration phase. These results are examples of Case 3 of Section 4.3.2.4. In Fig.6b, Fig. 6e, Fig. 6g and Fig. 6j, in addition to generating the models in the exploration phase, the GP was able to generate the models of the action zones in the exploitation phase. Then, these models obtained in the exploitation phase are replaced in the first models obtained in the exploration phase (Case 1 of the Section 4.3.2.4). One of the advantages of applying federated learning can be observed in the cases of the Rastrigin (Fig. 6f) and Schwefel(Fig. 6i) functions. In these examples, the monitoring system generated a model in the exploration phase of each scenario. However, in the exploitation phase, the GP was only able to generate a more accurate model in some action zones. Therefore, in the first model generated, only the models of the action zones where it was possible to obtain the model of the WQP were replaced (Case 2 of the Section 4.3.2.4). Finally, there are the cases of the results of the Griewank (Fig. 6c) and Schaffer (Fig. 6h) functions, in which no model could be generated in the exploration phase because the minimum value of the range of length scale values was high to fit the GP (Case 4 of the Section 4.3.2.4). Therefore, the uncertainty value is 1 in all the map except in the coordinates where measurements were taken, where the uncertainty is 0. In the model of the WQP, in all the coordinates where no measurements were taken, the value of the mean is equal to 0.



(a) Ackley (b) Bohachevsky (c) Griewank (d) h1

(e) Himmelblau (f) Rastrigin (g) Rosenbrock (h) Schaffer

(i) Schwefel (j) Shekel

Fig. 6: Example of the operation of the AquaFeL-PSO with different contamination profiles. At the top of the figures are shown the movement of the vehicles, the initial positions (black dots), the final positions (red dots), and the uncertainty of the model generated by the GP. At the bottom of the figures, the model of the WQP obtained in the monitoring task is shown.

6 Summary of the results

The main findings of this work are discussed below:

- The Uncertainty algorithm focuses on the exploration of the water resource surface. Because of this, it is not possible to accurately detect the contamination peaks of the action zones. However, it generates good models of WQP of the entire water resource.
- The Contamination algorithm, unlike the Uncertainty algorithm, focuses on exploiting areas with high contamination peaks. However, since it does not have the capacity to cover part of the surface of the water resource, it does not have the capacity to detect all the contamination zones and all the contamination peaks. In addition, ASVs can get stuck at a local maximum by not exploring the surface sufficiently.
- The AquaFeL-PSO was able to generate good models of the action zones and obtain the most accurate WQP models. It also obtained the best results in detecting contamination peaks in the action zones. This is due to the change of focus of the monitoring system and the distribution of the fleets in different action zones.
- In four benchmark functions used in this work, the GP converged at all nodes or sub-populations in the exploitation phase, enabling the generation of more accurate models of the WQP in the action zones. These functions are the Bohachevsky, Himmelblau, Rosenbrock and Shekel functions.
- By applying the Federated Learning technique it was possible to replace the models of the WQP generated in the sub-populations or nodes where the GP converged and to keep the data from the action zones of the first model in the nodes where it was not possible for the GP to converge. This advantage of the FL could be observed in the AquaFeL-PSO result with Rastrigin and Schwefel functions as ground truth.
- In functions such as Ackley and Schewefel, the GP was not able to converge in the exploitation phase at the nodes. However, in the exploration phase, it was possible to generate a first model of the WQP of the water resource, which was considered as the final model when the GP did not converge.
- Due to the large variability of the data in the near coordinates in the ground truths of the Griewank and Schaffer functions, the GP was not able to converge with the selected configuration. The length scale value was high for these functions. However, the scenarios presented with these functions are very unlikely scenarios to happen in real life, since the variability of water parameters at near coordinates is normally not expected to be large.

7 Conclusions

This work consists of the evaluation of the performance of the AquaFeL-PSO in ground truths of different benchmark functions, also called contamination profiles. The objectives of the evaluation were the detection of contamination peaks and the generation of accurate models of areas with high pollution levels and modeling of the entire water resource. In addition, the results of the AquaFeL-PSO were compared with two variants of the Enhanced GP-based PSO [25], the Uncertainty algorithm and the Contamination algorithm. The Uncertainty algorithm bases the movements of the ASVs on the control parameter of the Enhanced GP-based PSO and the model uncertainty term, which allows the ASVs to traverse unexplored areas of the water resource. In contrast, the velocity in the Contamination algorithm is calculated with data from the control parameter and the maximum contamination term, so the ASVs are guided to areas where contamination is high. The results show that AquaFeL-PSO was able to obtain models of the WQP of the water resource in eight of the ten benchmark functions evaluated. Regarding the generation of the models, by a small difference, the Contamination algorithm generated the best models of the action zones. However, the AquaFeL-PSO obtained the best performance in the generation of the model of the WQP of the whole lake and in the detection of contamination peaks. The results demonstrate the great performance of AquaFeL-PSO in different contamination profiles. From this, the development of a PSO and GP based monitoring system capable of multi-target problem solving, where each target is a water quality sensor, is proposed as a future research direction. In other words, the movement of ASVs should be based on data from several water quality sensors simultaneously.

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