Applications of Optimization Particle Swarm in Oceanography

Ana Alcantara, Marcelo Silva

Abstract – Oceanography is a field of study that seeks to analyze and understand the oceans' behavior, the planet they are part of and the living organism that depending on them, using, for this, scientific methods. As the oceans cover 71% of globe surface, they are a key element for the maintenance, existence and certainly the origin of life on Earth. The particle swarm optimization (PSO), a relatively new algorithm of Natural Computing, developed from the behavior of a flock of birds, has been applied in several areas. This is happening because of its simplicity, robustness and success in problems that use a large quantity of input data. This work approaches several applications of PSO in Oceanography, for example: Detection and characterization of thin layers of the oceans phytoplankton, prediction of growth of algae in port areas, prediction of trajectories of cyclones, weather forecast, sonic exploration of the oceans bottom, exploration of oil and gas in deep waters, reduction of greenhouse, among others.

Index Terms - Particle Swarm Optimization, Oceanography, Bioinspired Computation, Swarm Intelligence, Natural Computing, Oceans, Algorithm.

1 INTRODUCTION

THE oceans have a territory twice as large as the surface of the Moon and Mars together. With an average depth of 3.9 km, is a continuous three-dimensional environment, with about 1,370 million cubic kilometers, home to 95% of the Earth's biosphere and, in genetic terms, most of its biodiversity. It was in this vast environment that life arose billions of years ago and ever since has diversified suffering countless episodes of expansion and contraction [24].

The future of mankind is totally dependent on physical behavior, biological, chemical and geological oceans. Where, in addition to being a climate moderator and liven the greenhouse effect through absorption of large amounts of atmospheric carbon dioxide, producing about 90% of the Earth's photosynthesis ensuring the existence of oxygen in our atmosphere through the microscopic algae floating near their surfaces [18]. Inserted in this context there is a growing concern for the preservation and conservation of the oceans as a whole, it is a worldwide issue, extremely important. Obtaining new information about their behavior has contributed to shaping and expansion of knowledge on these aquatic systems and hence to maintain the balance of the planet. The oceanography, in turn, is the discovery process of unifying principles on data obtained in research in the ocean, the existing forms of life and land areas that limit. They involve various disciplines that integrate the fields of geology, physics, chemistry, biology, engineering, computing, as all apply to oceans and adjacent environments.

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With the advancement of technology, techniques and increasingly sophisticated tools has encouraged the development of multidisciplinary oceanographic research [9].

In recent years, Bioinspired computational techniques have been employed in oceanography and related areas successfully comparable to conventional computational techniques.

One such technique is the PSO (Particle Swarm Optimization), an optimization algorithm based on swarm inserted into a subarea Computer Bioinspired. This area has shown very promising results in terms of robustness, finding solutions, solution speed and numerical accuracy. Many of this success is due to the simplicity, versatility, generally parallel algorithms and ease of mathematical modeling of certain problems.

This article aims to show the state of the art, the past two decades, the iteration between oceanography and PSO, turning this optimization algorithm based on collective behavior in a powerful and important tool for the study oceanography.

2 BASIC CONCEPTS

Terminology natural computing has been used in the literature to describe all computer systems developed with inspiration or use of any natural or biological mechanism of information processing [2]; [14]; [13]; [4]. Natural computing can be divided into three sub-areas: (i) computing with natural mechanisms; (Ii) studies on the nature through the computer; (Iii) computing inspired by nature. With the objective: to develop mathematical and computational tools to solve complex problems in various areas of knowledge; design (computer) devices that simulate, emulate, models and describes natural systems and phenomena; synthesizing new life forms, called artificial life; and use natural mechanisms, such as strands of DNA and genetic engineering techniques, and new computing paradigms. These new paradigms have additional and / or complement existing computers based on silicon technology and von Neumman architecture. The swarm intelligence is a subdivision of natural computing, inspired collective behavior observed in nature, developed in the late 1980s the term "cluster" is used generically to refer to any structured collection of agents able to interact [3]. The main properties of a system based on collective behavior of clusters are: (i) proximity: the agents must be able to interact; (Ii) quality: the agents must be able to evaluate their behavior; (Iii) diversity: it allows the system to react to unexpected situations; (Iv) stability: not all environmental changes should affect the behavior of an agent; (V) Adaptability: ability to adapt to environmental changes. Therefore, a swarm system is one comprising a set of agents capable of interacting with each other and the environment, resulting in such properties [22].

3 OPTIMIZATION PARTICLE SWARM

The PSO was introduced in Computational literature by James Kennedy and Russell Elberhart in 1995, based on a population of individuals capable of interacting with each other and the environment, taking as examples: species of birds, schools of fish, and even behaviors human social. Based on the properties of self-evaluation, comparison and imitation, individuals are able to handle a number of possible situations that environment presents to them. The global behavior are therefore emerging results of these interactions. Thus the PSO search the simulation of these naturally simple activities, but mathematically complex [28].

In this article the PSO is specifically studied around the behavior of birds flock of species, due to its great usability in oceanographic area.

3.1 Mathematical Model

The PSO algorithm tries to emulate the following scenario to solve optimization problems: a group of birds are looking for food randomly at nearby locations. There is only a source of food in the area where it is being carried out the search. No bird knows where the food is, but they know how far is the food at each iteration time (considering a discrete time). Therefore, the best strategy to find the food is to follow closely the bird. In PSO, each separate solution corresponds to a bird in the search space, called particle. All particles have results (fitness) that are checked using the objective function, and have speeds that direct the flight of the particles. The particles fly through the problem space by following the particles that have the current optimal solution. Based on these behavioral observations, it can be concluded that the group's behavior is influenced by the experiences of results obtained by each individual and with the experience gained by the group [16].

Initially, the system contains a population of candidate solutions possible with random positions. Each of these particles is assigned a speed and particles start to move through the search space. In Figure 1 is shown a particle swarm randomly generated within the problem of the search space.

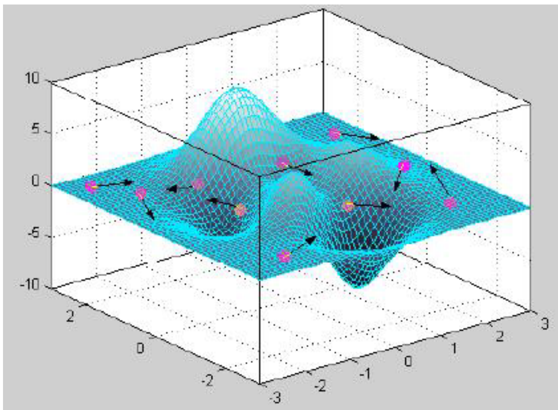

Figure 1: Illustration of a test particle

The speed of each particle (Vi) is modified considering two information (components) : the first is the best place to have passed throughout its history (your best position , pbest) ; and the second is the position of the best particle (social component, gbest) elected every generation step, that is, the trajectory of each individual within the search is dynamically adjusted by changing the speed of each particle according to its own search experience and the search experience other particles in space. In terms of optimization, this means a faster convergence of the particles in that neighborhood for a common solution [22]. Figure 2 illustrates a case where the particles together converged to the next region of a great, after successive iterations.

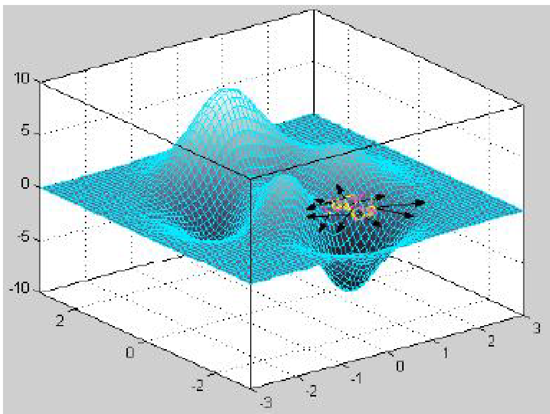

Figure 2: PSO convergence illustration

Equations (1) and (2), respectively, represent updates the speed and position of the observed particles:

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$$vij(t+1) = wvij(t) + c1r1(t)(pbesti(t)ij - xij(t)) + c2r2(t)(gbest(t)j - xij(t)),\ j = 1,2,\ldots,d \quad (1)$$

$$xij(t+1) = xij(t) + vij(t+1),\ j = 1,2,\ldots,d \quad (2)$$

where vij is the velocity of the particle i. xi is the current position of the particle, w is the value of inertia, cognitive c1 is the acceleration coefficient, c2 is the coefficient of social acceleration, R1 and R2 are numbers generated randomly and uniformly distributed in the interval [0,1] for each dimension j, pbesti is the best position already visited by the particle and gbest is the best position already visited by swarm [19].

4 OPTIMIZATION APPLICATIONS IN PARTICLE SWARM IN OCEANOGRAPHY

The oceanographic community, for its interdisciplinary nature, has great interest in the development of other fields, including in the area of computing, with new technology and computational methods and the PSO has fulfilled these expectations contributing to numerous applications, reducing the dimensionality of the data and presenting more accurate results. The following are some of them developed in the last two decades, selected because of their importance.

4.1 Monitoring and Forecasting Phytoplankton Growth

4.1.1 Detection and characterization of thin layers of phytoplankton

Popularly known as algae, phytoplankton does not have their own movements able to oppose the water moves, it is the main primary producer of the oceans, setting the photosynthetic activity in the photic zone, the initial organic matter that will allow the operation of almost all marine food webs, besides being the largest producer of oxygen on earth. His mapping is fundamental in multiareas oceanography [12]. Vilamala in 2010 developed a hybrid system - based on optimization particle swarm (PSO), and case-based reasoning (CBR) - for the detection and characterization of thin layers of phytoplankton using optical data obtained by hyperspectral sensors. The system operates in two stages. At first, the system locates the thin layers of phytoplankton PSO using CBR and the second uses to determine the characteristics (class, thickness and concentration) of thin layers of phytoplankton. For sensors that are used to capture the optical properties of each element in a given sample of water. During the course of oceanographic probe - using water samples collected from a limited number of vessels (around 10) - the system is able to report: (i) the amount, depth, and the characteristics of the thin layers of phytoplankton, and (ii) the time the containers collecting water samples should be closed. Every descent trajectory of the probe, the PSO is triggered by reducing the dimensionality of the data and presenting the most accurate results on the detection and location of thin layers. The PSO using as input parameters of the radiation coefficients at different depth levels along the path taken by the probe and has as a result the local maximum that will be used as an estimator of thin layers concentrations. The results obtained by the author confirms the ability of the CPS to map the distribution of phytoplankton from hyperspectral information using a variety of hypothetical oceanic environments. The CBR's ability to incorporate prior information to adapt to new situations was crucial for estimation and forecasting results on the classification of algae group and calculations on the thickness and concentration of the thin layer made using hyperspectral optical data. Figure 3 shows a simulation of the PSO exploiting the marine environment [30].

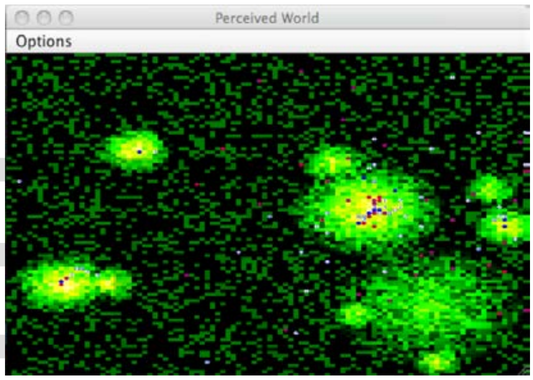

Figure 3 – PSO simulation exploring the marine environment

4.1.2 Forecast growth of algae in port regions

Through photosynthesis, the phytoplankton produces the oxygen that is necessary for survival of various communities of the aquatic environment [26]. However, depending on the oxygen concentration in the water, algae can become dangerous, producing toxic substances that can eliminate much of the local biodiversity, causing enormous damage. The forecast increase in algae is beneficial for fishing and environmental management because it allows fish farmers to gain more time to take appropriate preventive measures. At the Port of Tolo in Hong Kong due to the dumping of municipal waste and livestock, there was a nutrient enrichment in the aquatic environment, and consequently an increase in the amount of algae in the region, causing massive fish deaths over the past two decades. Causality and the dynamics of algae, still not very well known but it is known that are related to various factors such as chlorophyll-a, phosphor lag time, nitrogen, dissolved oxygen, depth of the Secchi disk, rainfall, temperature water, solar radiation, wind speed and tidal range, among others. Chau in 2005 developed hybrid systems based on RNA and PSO to the

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algae growth forecast in the Port of Tolo area, using the 10 aforementioned factors related to chance and dynamics of algae, as input variables for training networks neural multilayer perceptron with a hidden layer (Figure 4). Networks based on PSO were trained and validated using real data of water quality collected weekly at the Port of Tolo, from 1982 to 2002. The data sets of training, testing and validation were normalized in the range between 0 and 1, using the maximum and minimum values of the input and output patterns. Three models of networks Perceptron based on PSO - with 10-5-1 topologies (Figure 4), 5-3-1 (having as input variables: time of chlorophyll-a lag, phosphorus, nitrogen, dissolved oxygen, depth Secchi disk), and 1-3-1 (single input variable: chlorophyll) - were compared with perceptron networks with the same topology trained using the back propagation algorithm. The perceptrons based on PSO showed much faster convergence and greater generalizability that based perceptron the back propagation algorithm. All models showed a correlation coefficient greater than 0.92, using the training sets and validation for weekly and bi-weekly predictions about the growth of algae in Tolo Harbour in Hong Kong [6].

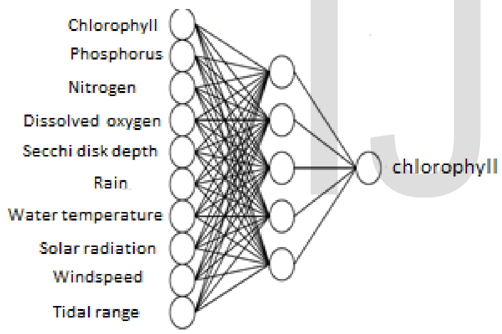

Figure 4 - Multilayered Neural Network

4.2 Trajectories Identification Cyclones.

Some studies indicate that increasing the temperature of ocean waters could be related to the intensity of cyclones since they are formed under special conditions in the ocean environment due to the water temperature and intensity of winds. Although these temperature conditions are natural, cyclones can be considered an indirect consequence of global warming, as well as being the most powerful atmospheric formations of nature. A medium intensity cyclone produces energy equivalent to the US electricity consumption for six months. The rains caused by the phenomenon are also outsized. During the passage of a cyclone for Jamaica was recorded rainfall of 2,400 mm in a period of four days. The weakest type of cyclone, called Tropical Storm (Figure 5), is strong enough to cause serious damage, sometimes even greater than those caused by more intense cyclones. In Texas, a tropical storm with winds of 110 km / h brought together hailstones the size of tennis balls.

Figure 5 - Tropical Cyclone Fay, Northern Australia

Identify the trajectory of tropical cyclones greatly increases these consequences. Rabeharisoa and colleagues in 2002 developed a self-adaptive model for cyclone trajectory forecast, which was insert a PAT tree (Main Axis Tree). The PAT tree allows the division data set efficiently in terms of speed to determine the nearest neighbor. principal component analysis was used to construct an efficient search tree. Thirteen predictors were used: the current positions of similar cyclones (longitudes and latitudes), the zonal and meridional displacements with delays of six hours per twenty-four hours and day of the year. The number of predictors was reduced to six with principal component analysis (PCA) using the Matlab software. Neural Network Linear Local Wavelet (LLWNN) with topology 6-6-1 trained with the PSO algorithm used was to cyclone trajectory predictions using data from three river basins (basin of Australia, basin of the South West Indian Ocean and the Atlantic basin). The model errors were measured by calculating the distance between the real position and the prediction position at a time six hours. The objective function was the mean square error (RMSE). Using the model proposed by the authors to forecast cyclones trajectories, the neural network based on PSO LLWN allowed stable forecasts. The network prediction LLWNN stability due to its flexibility and good generalization capability [25].

4.3 Weather forecast

The oceans play a vital role in relation to weather time, because the atmosphere is constantly in touch with the ocean and not the land more than 72% of the globe's surface. The circulation system of large ocean currents is essential for the establishment of the existing weather pattern, because the movement of hot water at the ocean surface acts directly on the atmospheric temperature. Changes in the length of the seasons can have a huge impact on the environment. Predict these climate change is critical to making decisions that allow nullify major impacts in human life. Time-use systems use very complex combinations of numerical tools for the study of the forecast. Because of phenomena on the global climate, such as the greenhouse effect, the classical models, not adaptive, can be very effective in weather forecast. To get around this, heuristic approaches, such as evolutionary algorithms and algorithms of collective intelligence, has been used in meteorological forecasts.

4.3.1 Discovery models in weather data

Esfandeh and Sedighi Zadeh in 2011 used a model based on STEPPING for weather forecast. The authors conducted two experiments using the toolbox Meteolab Matlab ® version 6. In the first experiment used data from observations of temperatures collected every 10 days between 1 January and 31 December 1999 in Rennes, France. In the second experiment used a set similar to the first experiment formed by precipitation data in Ostersund Froson, Switzerland, during the year 2001. The data observed in the second experiment showed many null values (corresponding to dry days), with high occasional peaks, making the second set of data more difficult to work than the first. The authors compared the results from the two experiments using the model based on PSO with results obtained using neural networks built in the toolbox Netlab. In the second experiment, the average error of the solution based on neural networks was equal to 3.03; while the average error of the PSO-based model was equal to 2.01. The results showed the superiority of the model-based prediction of the PSO and its ability to uncover hidden patterns in sets of soft and steep data [11].

4.3.2 Forecast of monthly rainfall in rainy seasons

A non-linear hybrid model based on PSO-ANN was proposed for monthly forecast of rainfall in rainy seasons. The proposed model differs from traditional models in the following aspects: (i) the input factors of hybrid PSO-ANN were selected from a large number of highly correlated factors of the previous period. The method of empirical orthogonal functions (EOF) has been used to effectively condense the information relevant to the predictors; (Ii) the best capabilities for determining the structures and generalization of neural networks trained using the PSO model. One example was the rain forecast for flood period of 37 base stations in Guangxi. Model forecast for the months of June to September 2009 were compared with actual observations obtained in the field. The results show the effectiveness of the predictions of the hybrid model developed by the authors [32].

4.4 Sonic exploration of the ocean floor.

The sonar system is capable of emitting sounds and capture their echoes, thus allowing to check the position of objects that are in your way, by measuring the time between the emission of sound and the reception of its echo. Thus, among other things, it is possible to study the ocean floor, collecting important data. Thompson et al in 2003 used a neural network trained to mimic an underwater acoustic model in an attempt to determine ocean floor parameters. The problem to model the acoustic properties of an underwater environment from a set of parameters of a sonar system and an additional set of environmental parameters can be solved by using intensive computing simulation. To this end it is desirable to reverse the template such that, given a certain state of acoustic underwater environment, along with system parameters and certain known environmental parameters is possible information about the unknown parameters environment. Due to the computational complexity of the acoustic model, however, it becomes an arduous task to perform in real time.

The application of neural network to emulate the underwater acoustic model reduces the amount of computing resources required to run the problem, and certainly helps a lot in the task of reversing the model. The problem remains, however, with regard to the reversal of neural network itself. A search in the input space is performed to determine the "best" set of environmental parameters, where "best" is measured by how well the result coincides with respect to the acoustic properties of the underwater environment measures.

Thompson et al (2003) have proposed two different inversion methods for neural network. Both involve the use of particle swarm optimization method (PSO) modified to provide significant improvements in the performance of the algorithm in solving the proposed problem.

The first method, called PSO2, proposes an approach which essentially approaches the gradient at a local point and decide which of the two step sizes will have to make based on this information this algorithm, each agent takes two steps in the same direction: one in standard PSO mode and another a distance much shorter. Then, the algorithm simply calculates the slope of the start point to each point and selects the step corresponding to a negative slope. The only additional parameter that is introduced into the system is the step size relative to the size "regular" pattern PSO step.

The second method, called CPSO proposes an amendment to the PSO based groups ("cluster"). The central idea is to force a kind of hierarchical structure to the cluster model, creating groups of agents moving over the search space keeping them relatively close. This is in contrast to the PSO standard, in which each agent is essentially autonomous. Thus, conceptually, there is the global search performed by each group (which is designed to behave like a standard particle swarm agent),

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and local search performed by internal agents of each group.

The model used to simulate the environment geo-acoustic has thirty entries: three parameters of sonar system 27 and environmental parameters including wind speed at the surface, bathymetry and the speed of sound at different depths in the water column. The output layer of the neural network neurons is 599, corresponding to 599 points in a series of underwater acoustic reverberation temporal levels. This is the input signal of an active sonar receiver due to inhomogeneous scattering in the ocean environment, including the surface and the seabed.

Figure 6 presents results of typical cases: a case where CPSO exceeds PSO2 another that exceeds PSO2 CPSO, and a third in which all three methods can find the global minimum very well. It is important to note that standard PSO almost never exceeds one of the other two algorithms. The results show that the two modified versions of the PSO proposed by the authors are efficient and reliable to perform the reversal of an underwater acoustic model based on neural network to obtain relevant parameters to the ocean floor features [29].

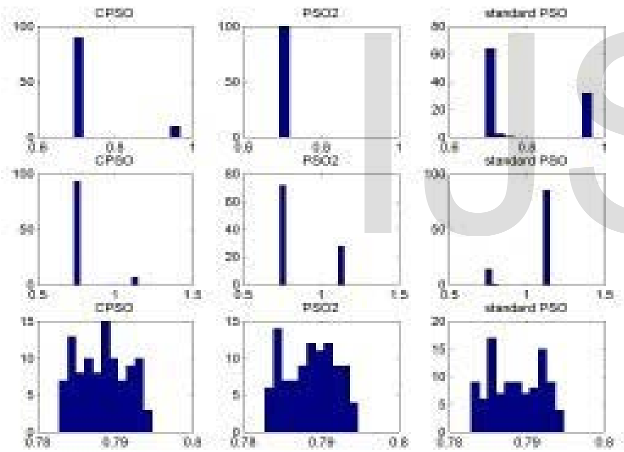

Figure 6 - Typical RMS error of inversion results over around 200 outputs a single operating point. On top PSO2 wins, the CPSO center wins and bottom three performing well (Thompson et al., 2003).

4.6 Oil Exploration Deepwater

4.6.1 Enhancement of traction levels of the anchoring systems

With the discovery of marine oil fields in increasingly deep water, the use of exploration and exploitation platforms supported by rigid and fixed to the bottom structure become impractical. According to Albrecht (2005) oil exploration at sea, as mentioned above, is a relatively new activity from the technological point of view and many borders are still to be overcome. From the point of view of the anchoring systems, especially in Brazil, one of these boundaries is increased depth of lease where the unit will operate. Figure 7 shows the evolution of the Brazilian oil production from 1982 to 2002. One can clearly see the increasing importance of deepwater fields (> 400m).

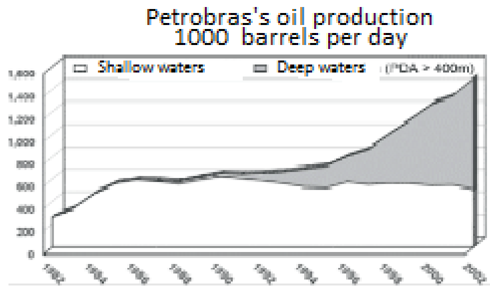

Figure 7 - Oil production evolution (ALBRECHT, 2005).

To improve the levels of tensile anchoring systems, Albrecht developed four optimization models using: (i) genetic algorithm (GA Classic); (Ii) micro genetic algorithm; (Iii) particle swarm; (Iv) evolutionary strategy. The PSO algorithm was implemented with the overall strategy (GPSO) and update the speed and position. There were implemented or the factor of constriction, or the local strategy (LPSO). For PSO was created the concept of system power. The power decrease means that the method is converging when the energy increases there is divergence occurs and what is called "system of explosion" [7]. A comparison of results obtained with various methods, suggests that optimization methods based on evolutionary algorithms, especially the PSO are recommended for use in optimization anchoring systems, achieving a significant improvement in the tensile levels on which systems work. PSO is recommended not only for the improvement in the systems traction levels, but also for its simplicity [1].

4.6.2 Detection of minimum displacement of floating platforms

New solutions have been developed to enable the exploration offshore in depths greater than 400 meters and now come to 2000 meters. In these depths it becomes impossible to use conventional compounds of chains and wire ropes systems and the adoption of new materials, such as polyester, as well as the adoption of systems which work under traction, with short radius, become feasible. One of the solutions used in deep waters is the use of anchored floating units. Thus the conditions of projects and operations platforms tend to become more and more complex and critical, less time and higher costs. This leads to the search for optimization tools that provide safety and efficiency projects at sea. The tool was Particle Swarm optimization with the goal of finding minimum displacements for platforms, having as input variables the radius of the mooring system and azimuth

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lines. To implement the PSO was used as a stopping criterion in the experiments the average fitness value greater than or equal to 95% of individual best for three consecutive generations. In order to facilitate the installation of mooring systems in an actual case, the optimal distance lines located in the same corner should be equal. For this purpose, the grouping of anchor lines at each corner is considered in the optimization process.

The results of the system are presented indicating that this method is effective and can be increasingly used and optimized. Table 1 shows the input variables of the original model and the optimized [21].

Table 1 - Comparison of input variables of the original model and the optimized model.

Line	Original Model			Optimized Model		
	Radius	Azimuth	Traction	Radius	Azimuth	Traction
1	3950.0	305.0	1972.4	2942.6	313.3	2128.3
2	3950.0	325.0	1972.4	2942.6	333.3	2128.3
3	3950.0	35.0	1972.4	3000.0	29.4	2131.0
4	3950.0	55.0	1972.4	3000.0	49.4	2131.0
5	3950.0	125.0	1972.4	3000.0	131.7	2614.1
6	3950.0	145.0	1972.4	3000.0	151.7	2614.1
7	3950.0	215.0	1972.4	2601.0	214.5	2608.7
8	3950.0	235.0	1972.4	2601.0	234.5	2608.7

4.6.3 Determining the location and the ideal type of new oil and gas wells

Among the waste produced by oil well exploration activity, two are worth mentioning because of its importance as pollutants: (i) the drill cuttings generated due to the soil drilling in search of oil reservoirs and (ii) the production of water derived from the production and activity resulting, among other things, preliminary treatments performed on the crude oil. Potential adverse effects of an improper disposal of cuttings and drilling fluids include: (i) pollution of the marine environment; (Ii) degradation of water and topsoil; (Iii) contamination of the subsoil [17]. The sustainability of the marine environment is an aspect that should be covered in all projects and enterprises today, involving oil exploration and production activities.

In this context, determine the location and the ideal type of new wells is an essential component in the efficient development of oil and gas fields. Optimization is a challenge because many wells can be vertical, horizontal, misappropriated, multilateral, among others. The computational demands for this problem are substantial and each includes a simulation. It is essential, therefore, that the optimization is done by an efficient and robust algorithm.

Onwunalu and Durlofsky in 2009 used the optimization algorithm particle swarm (PSO), to determine the best location and the best kind of well. Four cases were considered: drilling vertical wells, deviated wells and multi-lateral wells and optimization of single and multiple reservoirs perforations. For each case, both the PSO algorithm as the widely used genetic algorithm (GA) was applied to maximize the present network values. Multiple runs of both algorithms were performed and the results were calculated by averaging in order to make valid comparisons. It was shown that, on average, exceeds the PSO GA considered in all cases, although the relative advantages PSO vary from case to case. In total, the results were very promising and demonstrate the applicability of the PSO for this challenging problem [23].

6 CONCLUSION AND FUTURE WORK

The oceans are the largest biodiversity of the planet holders and are involved with phenomena indispensable for the maintenance of life on Earth. Therefore, the study, preservation and conservation of the oceans are unavoidable commitments to be made to future generations.

In this context, oceanography has become increasingly important and stimulated the development of new technologies and applications related to knowledge and sustainability of the oceans.

In the last two decades, the technological convergence between oceanography and natural computing has become a reality.

The PSO has shown extremely promising results in terms of robustness, finding solutions, solution speed and numerical accuracy. Much of this success is due to the simplicity, versatility, generally parallel algorithms and ease of mathematical modeling of some problems, so it has been increasingly used and inserted into the oceanographic study where future work may improve their distinct approaches to reversal of underwater acoustic models based on neural network and improved obtainment relevant parameters to the ocean floor features contributing to the study of their morphology. Another promising use is the optimization of PSO in the forecast models, justified in their superiority in such models and their ability to discover hidden patterns in sets of soft and steep data, thus making such important allies heuristic approaches in predicting climate changes can impact the environment and people's lives. Another improvement would be to optimize the PSO in mapping the distribution of distribution of photosynthetic organisms photic layer enabling the realization of analyzes both biological and physical and chemical, thus contributing to important oceanographic analysis.

Being a relatively new algorithm, the PSO must still receive many extras and have their performance improved, large-scale increasing its use in oceanography.

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