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OPTIMIZATION OF *CHLOROPHYLL A* REMOVAL FROM WASTEWATERS USING BIO-INSPIRED ALGORITHMS

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Abstract

The bio-inspired algorithms are versatile approaches that can be applied to a variety of problems. However, their efficiency is influenced by a multitude of characteristics such as quality of final solution, consumed computational resources, diversity management, convergence, complexity of the problem being solved. Consequently, the issue of choosing the best approach for a particular problem is a difficult task. In this work, the performance of two bio-inspired algorithms, Differential Evolution (an improved version) and Differential Search, is tested on an electro-coagulation process applied for removing *chlorophyll a* from the final effluent of aerated lagoons in a wastewater treatment plant. Based on a set of experimental data, a regression model was generated to determine the correlations between the process characteristics and the remained *chlorophyll a*. After that, a set of simulations using the two algorithms were performed with the goal of determining the optimal conditions leading to a minimization of *chlorophyll a* in two different cases: i) when the interval for the process parameters is the same with the experimental data and ii) when limits on the process parameters were imposed (as a mean to reduce the resources consumed). The results obtained indicated that the two algorithms are able to provide acceptable results.

Key words: electro-coagulation, chlorophyll a, differential evolution, differential search

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1. Introduction

One of the biggest challenges of the last century with regard to issues such as population growth, deforestation, rapid urbanization, industrialization and warming global climate change is water resources preservation. Nowadays, due to these factors, the access to safe drinking water is limited. Therefore, in order to maintain quality and improve quantity while also ensuring environmental protection and sustainability, there is a stringent need to develop efficient technologies for treating and managing all types of wastewaters (urban, industrial and agricultural wastewaters). Also, more robust and efficient drinking water treatments are required when dealing with risks posed by environmental contamination. Electrocoagulation (EC) is a process that combines the benefits of coagulation, flotation

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and electrochemistry and it can be efficiently used for the treatment of drinking water and wastewater (Hakizimana et al., 2017; Lofrano and Meric, 2019; Moussa et al., 2017). EC is a green and eco-friendly process; besides, its reactions occur in a short time and investment costs are low (Ighilahriz et al., 2018; Mollah et al., 2001). The presence of algae in drinking water resources leads to change in taste, odour, and production of toxic materials. Moreover, the growth of algae in wastewater treatment plants causes suspended solid concentration to increase and exceed its standard (Fast et al., 2014). In the recent years, the EC method has been applied to remove algae from aqueous solutions (Fast et al., 2014; Uduman et al., 2011). However, the main downside of this way is the difficulty of optimizing the operating parameters as two or several parameters may react together and/or the relationship between response and one or a few factors is nonlinear.

In this work, an approach combining an improved version of Differential Evolution (DE) (that includes the opposition based principle, self-adaptation and a Local Search procedure), Differential Search (DS) and a statistical regression model is applied on an electro-coagulation process for the removal of *chlorophyll a* (as indicator of algae) from the final effluent of aerated lagoons in a wastewater treatment plant.

Because DE and DS are flexible and do not require special conditions for the properties of constraints and objective functions (Feoktistov, 2006), it can be effectively applied to solve the optimization of the electro-coagulation process. The objective is twofold: i) to efficiently optimize the considered process; and ii) to identify which of the two selected approaches is better suited for the problem at hand. As methodology, a regression model is first generated to determine the correlations between the process characteristics and the remained chlorophyll. Then, it was included into the optimization procedure in order to minimize the amount of *chlorophyll a*. Both optimizers provided a multitude of combinations leading to minimum values for *chlorophyll a*. However, DE tended to provide slightly better results (in term of the minimum: 1.16E-05 vs 8.97E-04) but DS had a higher exploration capability and generated solutions containing a higher variation in the process conditions.

2. State of the art

2.1. The electro-coagulation process

As it combines the benefits of coagulation, flotation and electrochemistry, EC is an emerging technology in water and wastewater treatment. EC is designed to work for any treatment capacity and has a series of advantages that leads to a good removal performance. For example, compared with chemical coagulation, the EC process generates lower quantity and more stable of sludge (Song et al., 2017).

In this process, since the electron is the primary reagent, there is no need for additional chemicals. Therefore, EC is considered as an environmentally friendly technology and many researchers studied the fundamentals and emerging applications of the EC technique in water and waste water treatment (Bazrafshan et al., 2012, Emamjomeh and Sivakumar, 2009, Garcia-Segura et al., 2017, Hakizimana et al., 2017, Kabdaşlı et al., 2012, Moussa et al., 2017, Song et al., 2017). This process has extensively been used to treat water and different kinds of wastewater. Most studies optimize parameters like electrode type, current density and other parameters effective in the process (Hakizimana et al., 2017). However, studies focusing on modelling the input and output variables of the system are still limited. Furthermore, microalgae harvesting by the EC process has attracted great attention of researchers across the world. An example of modelling is the study (Curteanu et al., 2011), where algal removal by the EC process is approached using different types of neural networks. Good results for the removal efficiency and other system parameters were reported proving that the neural modelling is an adequate modelling tool.

The theory behind coagulation/ flocculation and EC is basically the same. Both methods target the removal of particles from wastewater through destabilizing/ neutralizing the repulsive forces that keep the particles suspended in water. When the repulsive forces are neutralized, the suspended particles will form larger particles that can settle down for easier separation from water (Moussa et al., 2017). EC combines various mechanisms that can be electrochemical (metal dissolution and water reduction, pollutant electro-oxidation or electro-reduction), chemical (acid/base equilibria with pH change, hydroxide precipitation, redox reaction in the bulk) and physical (physical adsorption, coagulation, flotation). These can be sequential and/or parallel (Hakizimana et al., 2017). The EC process is based on the formation and aggregation of a colloidal system and its further coagulation enhanced by the use of the coagulating agents. Metallic and organic pollutants are separated from the aqueous phase by their precipitation with the coagulants and subsequently removed from the treated water. The aggregates formation is explained by the Derjaguin-Landau-Verwey-Overbeek theory where it is assumed that the formation of an aggregate depends on the interaction forces by the sum of Van der Waals and double layer forces (Garcia-Segura et al., 2017).

Although this process is utilized in many industries to remove different pollutants, the basis of contamination removal is nearly alike, which can be divided into five main mechanisms as follows:

(1) Metal ions (mainly aluminium and iron) are released from the sacrificed anode's surface with the exertion of electricity current to an electrochemical reactor.

(2) OH^- and H_2 ions are formed simultaneously on the cathode's surface.

(3) Polymeric species of aluminium and iron ions are formed in the solution.

(4) Pollutants and particles become unstable and accumulate and, in turn, flocks are formed via the mechanisms of electrostatic attraction and physical entrapment.

(5) Finally, the formed flocks are separated from the aquatic solution through two mechanisms: electro-flotation and sedimentation (Azarian et al., 2018, Mollah et al., 2001, Yavuz and Ögütveren, 2018).

The possible reactions over the process using the aluminium electrode are as follows:

Anode:

$$Al_{(s)} \rightarrow Al^{3+}_{(ag)} + 3e^- \quad (1)$$

$$2H_2O_{(L)} \rightarrow O_{2(g)} + 4H^+_{(L)} + 4e^- \quad (2)$$

Cathode:

$$2H_2O_{(L)} + 2e^- \rightarrow H_{2(g)} + 2OH^-_{(ag)} \quad (3)$$

Solution bulk:

$$2Al + 6H_2O + 2OH^- \rightarrow 2Al(OH_4^-) + 3H \quad (4)$$

$$nAl(OH)_3 \rightarrow Al_n(OH)_{3n} \quad (5)$$

Chlorophyll a reaction:

$Fe(OH)n$ or $Al_n(OH)_{3n}$ + *chlorophyll a* → removal by using sedimentation or flotation (6)

2.2. Optimization

In case of real-world processes, due to the complex interactions and high number of parameters (that not always can be correctly measured), the optimization problem is much difficult. Therefore, efficient approaches able to cope with all these aspects must be applied. Generally speaking, there are two main classes of optimizers: exact (deterministic) techniques and stochastic algorithms (Weise and Chiong, 2015). The majority of the exact optimizers are based on gradients (eq. Steepest Descent. Quasi-Newton etc.) and always find the same solution if they start from the same point (Mirjalili et al., 2017). On the other hand, the stochastic optimizers use stochastic operators and do not require derivatives. As a result, even if they start from the same point, stochastic optimizers provide different solutions, making them less reliable.

However, due to the randomness behaviour, they can avoid the local optima, this being one of the main advantages of stochastic algorithms (Mirjalili et al., 2017). For this type of algorithms, different classifications can be applied, the most encountered variants being based on: i) source of inspiration (biological, environment, human behaviour, physics, chemistry, etc.); and ii) number of random solutions generated at each step (individual based and population based). The majority of algorithms are population based and, in the latest years, a raising trend of developing new stochastic optimizers was observed. The majority of these algorithms are meta-heuristics, in the sense that they provide a general framework with a heuristic strategy for exploring the solution space (Sörensen, 2015).

The list of meta-heuristics optimizers is quite long, in the last ten years, more than 200 new algorithms being proposed. Table 1 presents some examples of algorithms, organized based on their source of inspiration. As it can be observed from Table 1, there are many meta-heuristics that can be chosen to solve the current problem.

Table 1. Example of meta-heuristic optimizers

Source		***Examples of algorithms***
Animals	Birds	Hummingbird Optimization Algorithm (Zhuoran et al., 2018); Emperor Penguin Optimization (Dhiman and Kumar, 2018); Seagull Optimization Algorithm (Dhiman and Kumar, 2019); Owl Search Algorithm (Jain et al., 2018)
	Mammals	Spotted Hyena Optimization (Dhiman and Kumar, 2017); Binary Artificial Sheep Algorithm (Wang et al., 2017); Rhino Heard (Wang et al., 2018); Squirrel Search Algorithm (Jain et al., 2019)
	Insects	Butterfly Optimization (Arora and Singh, 2018); Grasshopper Optimization Algorithm (Saremi et al., 2017); Pity beetle algorithm (Kallioras et al., 2018)
Simple cell	Viruses	Virus Optimization Algorithm (Liang and Cuevas Juarez, 2015); Virus Colony Search (Li et al., 2016)
	Eukaryote	Physarum Optimization (Liang et al., 2015);
	Prokaryote	Bacterial Gene Recombination Algorithm (Hsieh, 2014)
Plants		Artificial Algae Algorithm (Uymaz et al., 2015); Hybrid Artificial Root Foraging Optimization (Liu et al., 2017); Tree Growth Algorithm (Cheraghalipour et al., 2018)
Environ-ment		Rain-fall Optimization Algorithm (Aghay Kaboli et al., 2017); Lightning Attachment Procedure Optimization (Nematollahi et al., 2017); Farmland Fertility (Shayanfar and Gharehchopogh, 2018)
Human behaviour	Social behaviour	Queuing Search Algorithm (Zhang et al., 2018); Future Search Algorithm (Elsisi, 2019); Team Arrangement Heuristic Algorithm (Babayan and Tahani, 2019); Poor and Rich optimization algorithm (Moosavi and Bardsiri, 2019)
	Services	Market Competition Behaviour (Qiu and Liu, 2016)
	Music and sports	World Competitive Contests (Masoudi-Sobhanzadeh and Motieghader, 2016); Volleyball Premier League (Moghdani and Salimifard, 2018);
Physics		Optics Inspired Optimization (Husseinzadeh Kashan, 2015); Electro-Search algorithm (Tabari and Ahmad, 2017); Henry Gas solubility optimization (Hashim et al., 2019)

However, identifying the appropriate metaheuristic for optimizing a complex problem is not always an easy task as there are multiple traits that can be considered: quality of the final solution, efficiency, diversity management, convergence. In addition, the performance is also influenced by the characteristics of the problem being solved: convexity, derivability, non-linearity.

From the multitude of bio-inspired optimization metaheuristics the literature presents, in this work, two population based algorithms were selected: DE (Storn and Price, 1995) and DS (Civicioglu, 2012) and applied comparatively. The main reason for choosing these two algorithms consists in the fact that they proved efficient for a variety of problems. In addition, DE is well known and can be considered as a reference for the newer approaches (such as DS).

DE is inspired from the Darwinian principle of evolution and is one of the most popular algorithms from its class (Wu et al., 2018) because it has a simple structure, it is efficient and simple to use. Over the years, different strategies to improve its performance were proposed: i) use of adaptation and self-adaptation for the control parameters (Peñuñuri et al., 2016); ii) steps alteration (Sallam et al., 2017; Vaishali et al., 2018; Zhang and Zhang, 2017); iii) hybridization with other approaches (Ahandani, 2016; Cai et al., 2016; Nama et al., 2016). Two observations are worth mentioning regarding DE: i) although it is not a recent algorithm, it still proves its efficiency, exceeding many other algorithms; ii) as the mentioned literature shows, a lot of work is being done on DE, respectively, different techniques are applied for its improvement, thus obtaining new variants, with higher performances. As a result, in its simple form or combined with other approaches, DE was successfully used to solve a variety of problems from different domains.

In the area of environmental protection and wastewater treatment, examples of applications include: i) support for environmental decision making (Cortes et al., 2002); ii) design of a continuous ion exchange process for the wastewater treatment (Bochenek et al., 2011); iii) depollution of gaseous streams (Curteanu et al., 2014); iv) soil remediation (Sobariu et al., 2017); v) removal of heavy metals (Bleotu et al., 2018); vi) water quality monitoring (Yazdi, 2018). Compared with DE, DS is a newer algorithm. It is inspired from the Brownian motion of migrating organisms and shows a good potential for being better than the state-of-the-art approaches. As it is still in its infancy, its effectiveness was not fully tested on a variety of cases and only a few improvements and adaptations were proposed (Kumar et al., 2015; Liu, 2014; Liu et al., 2016). Similar to the other metaheuristics, DS is a flexible algorithm and can be used for various applications like: solar photovoltaic panels (Paital et al., 2018), image processing (Gunen et al., 2016; Kotte et al., 2018), reactive power dispatch (Abaci and Yamaçli, 2017), identification of the 2-Chlorophenol oxidation model (Chen et al., 2015)

3. Case study

3. 1. Wastewater properties and analysis

Bu Ali Industrial Town, Hamedan, Iran, has a waste water treatment plant (WWTP) containing an aerated lagoon system without sludge return. It receives the sewage of different industries (600 m^3/day) and its daily capacity is 800 m^3. The main treatment processes of this plant include preliminary treatment (screening), two aerated lagoons (complete mix reactors), and a sedimentation lagoon. At the end of the process, the effluent is chlorinated and used for agricultural usages. One of the problems with this plant is that it cannot meet the out standard levels because of algae growth, particularly in warm seasons. The properties of the effluent have been indicated in Table 2.

Table 2. Physicochemical characteristics of the Bu Ali Industrial Town WWTP effluent

Parameters	*Value*
Chlorophyll a/(mg/m^3)	*739±687*
COD /(mg/L)	*197±66*
TSS /(mg/L)	*150±63*
pH	*6.9±1.1*
Salinity /(mg/L)	*2323±1840*
TDS /(mg/L)	*2400±1900*

In order to detect the concentration of algae, a spectrophotometric method was used, according to the Standard Methods for *chlorophyll a* determination (Association and Association, 1989). Also, for measurement of COD and TSS, open reflex and gravimetric methods were applied, respectively. TDS and pH were determined using a lab pH-meter (from Hach Co).

3.2. Experimental setup

In this study, a 6-compartment pilot-scale reactor with continuous flow was used (Fig. 1). It should be noted that, since the concentration of algae changes during different hours a day because of sunlight, an equalization basin was used prior to the electrochemical reactor. The main reactions (Eqs. 1-5) take place in the first chamber (8 L) and sedimentation and separation occur in the second chamber (12 L). So as to study the variables, current density (0.7-12 A/L), hydraulic contact time (5 - 60 min), different distances between electrodes (1-3.5 cm), and electrode type (stainless steel and aluminium) with monopolar arrangement were operated. Moreover, the size and effective surface of the electrodes and flow rate were as follows: 14 x 24 cm, 3300 cm^2 and 10 - 100 L/h, respectively. In order to provide electricity, a DC power supply with the range of 0 - 100 A for current and 0 - 50 V for voltage (Adak, ps_405, Hamadan Kit CO, Iran) was used.

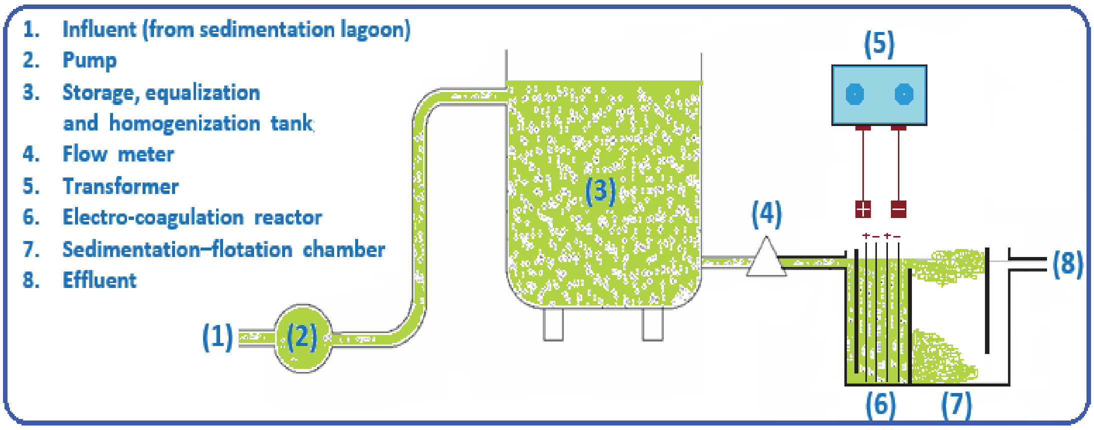

Fig. 1. A schematic diagram of the electrochemical reactor used in this study

A very important point here is that hydrogen micro-bulbs are generated on the surface of any cathode. In contrast, the mechanisms governing algae removal depend on the kind of anode. For instance, in the case of the stainless-steel electrode, oxygen gas is released from water electrolysis and, in turn, the main mechanism is electro-flotation by the generation of oxygen and hydrogen micro-bulb on the anode and cathode surface, respectively. When the aluminium electrode is used, aluminium ions are released and metal hydroxides, as well as different species of monomer and polymeric aluminium are formed, which are the main reason for electrocoagulation (Eqs. 1-6) (Azarian et al., 2018; Curteanu et al., 2011; Yavuz and Ögütveren, 2018).

The process analysis was done in different conditions of retention time (5-50 min) and using two types of electrodes based on aluminium and stainless steel, with different distances between electrodes (from 1.0 to 3.5 cm)

4. Process optimization

The complexity of the mechanism involved in the electrochemical process makes difficult the development of a phenomenological model, and, consequently, a regression model was determined. After that, a series of simulations were performed with DE and DS by varying the algorithms settings (various combinations of control parameters and a self-adaptive procedure) and the results were analysed and compared.

4.1. Differential search

In the DS algorithm, the population represents an artificial super-organism that migrates (Civicioglu, 2012). During the migration process, the members of the population (also known as artificial organisms) change their position, the decision to stay in a new position (stopover site) being determined based on the fitness function (Guney et al., 2014). This movement is repeated until a stop criterion is reached.

A simplified schema of the DS algorithm is presented in Fig. 2.

(1) In the first step, the DS parameters (population size and individual length) are initialized. If the size of the population (*N*) is user defined and can be changed at every run, the individual length is in close correlation with the problem dimensionality (*D*). For the initial DS algorithm, the length of the individual is equal to *D*.

(2) After that, based on a random number generator, the initial population is generated:

$$x_{i,j} = rand * (up_j - low_j) + low_j \qquad (7)$$

where *rand* is a randomly generated number in the interval (0,1), *up* and *low* represent the upper and the lower limits, i=1..N and j=1..D.

The evaluation of the individuals in the population is realized based on a fitness function. For the problem considered in this case, the fitness is represented by the mean squared error between the regression model predictions and the experimental data.

(3) In the donor selection step, a random shuffling procedure is applied in order to discover the stopover site and then the donor is randomly selected: $donor = x_{r1}$, where r1=1..N.

(4) In order to determine the stopover site, a set of parameters need to be reset: *scale*, p_1 and p_2. Scale controls the change occurring in the position of the individuals and is determined according to Eq. (8). The DS control parameters (p_1 and p_2) influence the degree of trial pattern mutation in comparison with the target patterns (Alkan and Balkaya, 2018) and their most suitable values are p_1=0.3*rand and p_2=0.3*rand.

$$scale = randg * (2 * rand1) * (rand2 - rand3) \qquad (8)$$

where *randg* is a random number generated with the gamma distribution and *rand1, rand2* and *rand3* are generated with a normal distribution.

(5) The stopover site is determined with Eq. (9):

$$s_i = x_i + scale * (donor - x_i) \qquad (9)$$

(6) If the fitness of the stopover site is better than the current position, the individual moves to the new position.

4.2. Differential Evolution

Similar to the DS algorithm, DE works with a population of potential solutions. The optimum is found by evolving the solutions (through mutation, crossover and selection) until a stop criterion is reached. Various studies (Al-Dabbagh et al., 2018; Dragoi and Dafinescu, 2015; Sallam et al., 2017; Vaishali et al., 2018; Zhu et al., 2016) showed that although the initial DE version proposed in (Storn and Price, 1995) is powerful enough to solve complex problems, its performance can be improved through the application of different approaches such as Opposition based Learning (OBL) (Tizhoosh, 2005), local search and/or self-adaptive control parameters. Therefore, in this work, an improved DE approach is used (Fig. 3).

(1) In the first step, the parameters (population size and individual length) of the algorithm are initialized. As this is an improved DE version, the control parameters (*F*, *Cr*) are automatically selected based on a self-adaptive procedure. This implies that the individuals forming the population contain these variables and they are modified using the same mechanism used for the other characteristic of the individual.

(2) Then, the initial solutions are generated using the same mechanisms as in DS case (Eq. 7). In order to improve this initial set of solutions, the OBL approach is applied. The individuals with the best fitness function are kept in the population, while the others are discarded.

(3) In the mutation step, a set of new individuals are generated based on the existing ones. The approach considered is called differentiation and, in this work, has the following form:

$$x_i^{mutated} = x_{base} + F(x_{r1} - x_{r2}) + F(x_{r3} - x_{r4}) \quad (10)$$

where: x_{base} is the base vector (which in this work is randomly selected from the population) and $r1$, $r2$, $r3$, $r4$ are randomly selected from the population ($base \neq r1 \neq r2 \neq r3 \neq r4$) and ordered based on the corresponding individual's fitness function from the best to worst.

(4) After that, the characteristic of the individuals from the mutated population and from the current population are combined using a binomial crossover. The resulting trial population is then evaluated to determine the fitness of its individuals.

(5) In the selection step, the current and the trial population are competing one to one, the winners forming the new generation.

(6) In the last step, the best solution found so far is identified and improved using the Local Search algorithm.

5. Results and discussion

Based on the experimental setup, a set of 44 points were gathered. The measured parameters and their statistical information are presented in Table 3, where, for the electrode type, 0 indicates aluminium and 1 stainless steel.

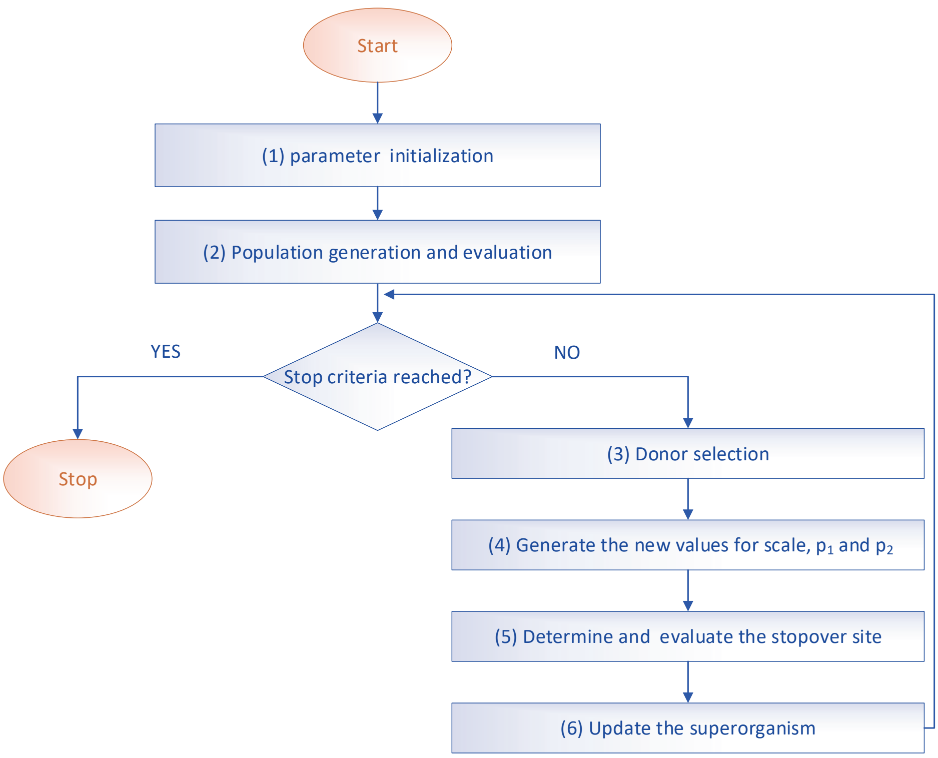

Fig. 2. DS general schema

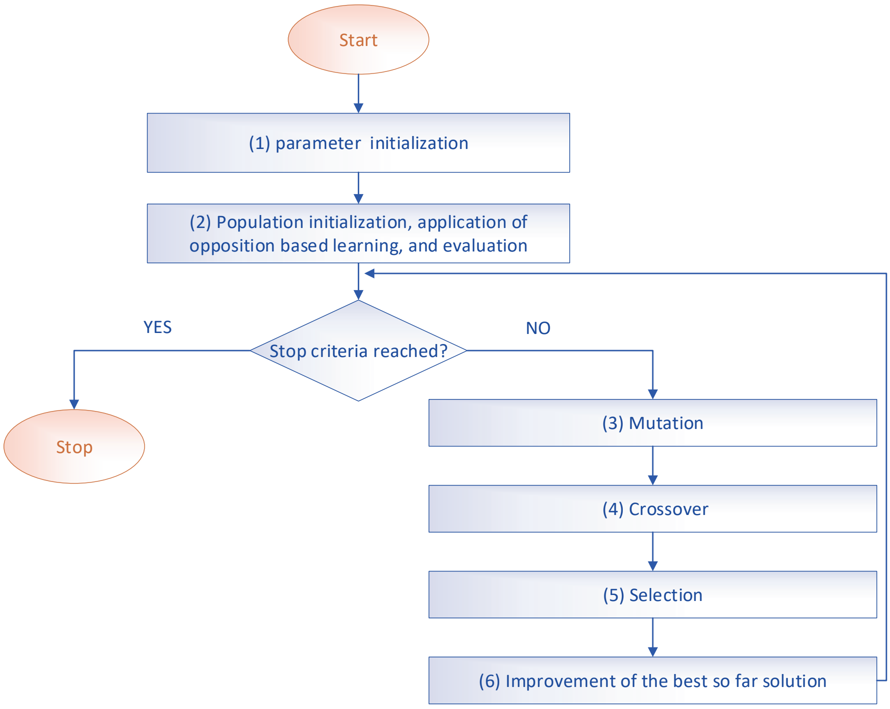

Fig. 3. General schema of the DE algorithm

5.1. Regression model

The regression model was determined based on the experimental data using Minitab 17 software. The objective was to generate predictions of the final amount of *chlorophyll a*, determined as function of initial values of *chlorophyll a* and operation conditions (electric power, time, electrode distance and electrode type). Initially, all order two interactions were considered. For this combination of process characteristics, the F-test (that displays the results based on the normal distribution and that is better than Bonett's test and Levene's test for normal distributions) indicates that the null hypothesis can be rejected and that the model provides a better fit than the intercept-only approach (Table 4). However, the p-value (the probability of making a Type 1 error) is higher than the significance value (0.05) for a multitude of sources. Consequently, these sources must be removed one by one until all sources have a p-value < 0.05. Table 5 presents the final combination that respects this condition (Eq. 11).

*Final_cholorophyll a = 397.9 -1.659*Power - 16.57 *Time + 0.0661*Initial_chlorophyll a +0.001251*Power*Power + 0.3065*Time*Time + 41.22*Electrode_distance*Electrode_distance - 8.45*Time* Electrode_distance – 3.97 *Time*Electrode_type +0.6421*Electrode_type*Initial_cholorophyll a* (11)

Table 3. Characteristics of the experimental dataset

	Power ($W\ dm^{-3}$)	*Time (min)*	*Electrode Distance (cm)*	*Electrode type*	*Initial Chlorophylla (mg/m^3)*	*Final Chlorophylla (mg/m^3)*
Minimum	50	5	1	0	550	0
Maximum	600	40	3.5	1	1415	1220
Standard deviation	117.9953	9.319231	0.4702	0.5	352.9903	389.0013

Table 4. Analysis of variance for all the order two combination of process parameters

Source	*DF*	*Adj SS*	*Adj MS*	*F-Value*	*P-Value*
Regression	14	6299331	449952	216.19	0
Power	1	21279	21279	10.22	0.004
Time	1	25911	25911	12.45	0.002
Electrode_distance	1	3835	3835	1.84	0.186
Electrode_type	1	2297	2297	1.1	0.303
Cholorophylla_i	1	13277	13277	6.38	0.018
Power*Power	1	31982	31982	15.37	0.001

Source	***DF***	***Adj SS***	***Adj MS***	***F-Value***	***P-Value***
Time*Time	1	19811	19811	9.52	0.005
Electrode_distance*Electrode_distance	1	12326	12326	5.92	0.022
cholorophylla_i*cholorophylla_i	1	12063	12063	5.8	0.023
Power*Electrode_type	1	1196	1196	0.57	0.455
Power*cholorophylla_i	1	3146	3146	1.51	0.23
Time*Electrode_type	1	19231	19231	9.24	0.005
Electrode_distance*Electrode_type	1	0	0	0	0.988
Electrode_type*cholorophylla_i	1	295782	295782	142.12	0
Error	27	56194	2081	-	-
Total	41	6355525	-	-	-

Table 5. Analysis of variance for the final regression model

Source	***DF***	***Adj SS***	***Adj MS***	***F-Value***	***P-Value***
Regression	8	6284417	785552	364.56	0
Power	1	89108	89108	41.35	0
Cholorophylla_i	1	10922	10922	5.07	0.031
Power*Power	1	22271	22271	10.34	0.003
Time*Time	1	21622	21622	10.03	0.003
Electrode_distance*Electrode_distance	1	121069	121069	56.19	0
Time*Electrode_distance	1	33200	33200	15.41	0
Time*Electrode_type	1	14704	14704	6.82	0.013
Electrode_type*cholorophylla_i	1	1749235	1749235	811.78	0
Error	33	71108	2155	-	-
Total	41	6355525	-	-	-

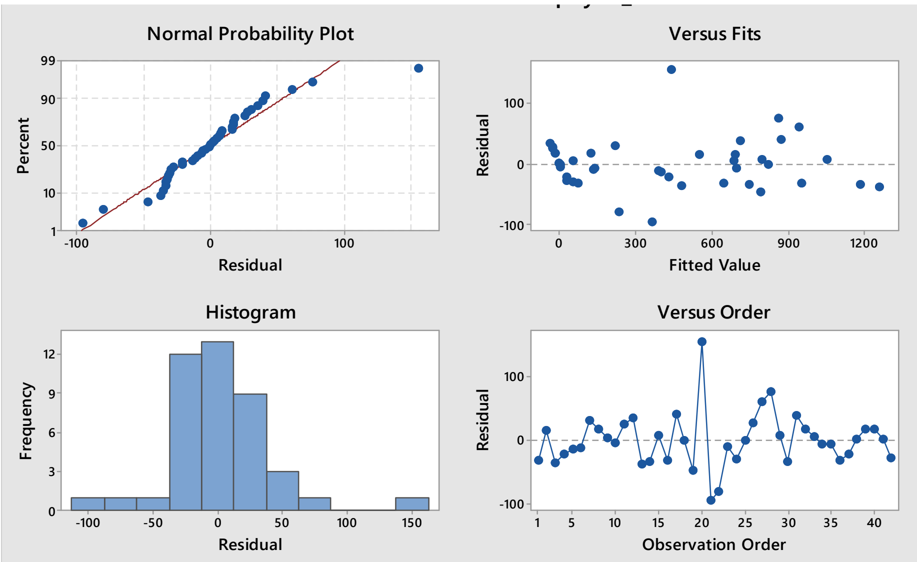

Fig. 4. Residual plots for the regression model

For the model represented by Eq. (11), the R^2 is 98.88% and R^2 predicted is 97.8%. In addition, the residual plots show that there is a good fit between predictions and experimental data (Fig. 4).

5.2. Process optimization

In order to determine the best conditions leading to the minimization of the *chlorophyll a* amount, the regression model (Eq. 11) was introduced in two optimization procedures and then the process was optimized considering two distinct situations: i) when no limits were imposed on the values of the process variables (free optimization) and ii) when limits were imposed to the power and time (as means to reduce the consumed resources). For the population based optimizers (such as DS and DE), a high diversity greatly contributes to the algorithm performance (Črepinšek et al., 2013). There are many types of diversity measures (that can be applied at phenotypic, genotypic or of combination of the two levels). In this work, the Euclidian distance for both the phenotype and the genotype was computed. Fig. 5 presents the evolution of population diversity during one run of DS and DE algorithms when population size = 20 and number of generations = 50.

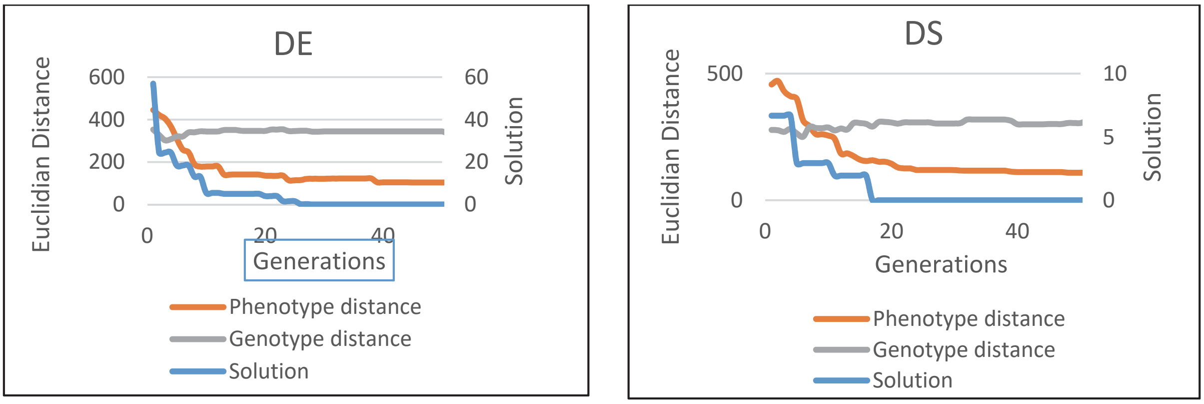

Fig. 5. The variation of genotype and phenotype Euclidian distance of population for a run of DE and DS algorithms

Table 6. Optimization results when no limits are imposed to the process parameters

Algorithm	*Power*	*Time*	*Electrode distance*	*Electrode type*	*Initial chlorophyll a*	*Final chlorophyll a*
DE	439.0825	17.10557	1.658527	1	674.05	1.16E-05
	273.1378	25.7525	2.955883	1	805.8041	3.32E-05
	113.0527	14.43881	1.736773	0	553.4427	4.88E-05
	181.1513	23.83266	2.464719	1	597.2389	6.65E-05
	56.75889	20.52621	2.311446	0	1269.269	0.000131889
	181.1439	23.83296	2.464157	1	597.2393	0.000191438
	63.41612	18.02164	1.750245	0	629.5137	0.000209039
	81.75216	18.12765	2.165013	0	1020.361	0.000273067
	66.4293	19.34524	1.913533	0	1127.098	0.000278022
	269.2604	34.54132	2.384222	1	1078.049	0.000328435
DS	569.0366	38.48206	1.829056	1	1319.474	0.000897
	441.9285	22.51206	1.631638	1	845.3106	0.001279
	82.3452	16.86449	1.638057	0	685.7981	0.002221
	249.9485	22.38937	3.342996	1	588.3224	0.003566
	357.9998	26.02614	2.215163	1	914.3702	0.006044
	157.6763	30.67182	1.957816	1	739.4357	0.006905
	145.191	14.16615	1.773388	0	1096.574	0.009847
	494.1183	15.86036	2.865394	1	579.8832	0.010892
	583.1663	23.74353	2.268303	1	991.3192	0.011091
	204.0818	13.50792	2.667839	0	1022.926	0.011521

As it can be observed, as the best solution found so far tends to go to the known optimum, the diversity of the genotype slightly varies (but tends not to decrease), while the diversity of the phenotype decreases (fact which indicates that the all solutions corresponding to the algorithm population are closer to each other – thus indicating convergence).

For each case, simulations with the two algorithms were performed with the same parameters as previously mentioned for diversity measurement. The results obtained are listed in Table 6 (when no limits are imposed), Table 7 (when the power is reduced to half) and Table 8 (when both power and time are reduced to half). In all cases, the optimization results obtained with DS tend to be higher than the ones provided by DE. This indicates that DE has a better ability to determine solutions in the vicinity of the optimum.

However, DE has a series of improvements which were not included in the DS. Consequently, using the same computational resources, DS is able to provide solutions that are very close to the ones provided by state-of-the-art approaches. By analysing the results from Table 7, it can be observed that for DE, the best solutions include a single type of electrode, while DS provides good solutions with both types of electrodes.

Table 7. Optimization results when power is max 300 (W dm^{-3})

Algorithm	*Power*	*Time*	*Electrode distance*	*Electrode type*	*Initial Chlorophyll a*	*Final Chlorophyll a*
DE	173.978	23.90775	2.162471	1	582.952	0.000020
	240.2209	8.534644	1.014559	0	1184.092	0.000024
	154.8637	13.52497	1.339635	0	1152.587	0.000039
	121.7448	14.9971	1.947845	0	840.3587	0.000172
	103.0692	16.99657	1.547172	0	1156.265	0.00018
	240.2348	8.528611	1.005121	0	1184.096	0.0002
	86.9473	38.15249	2.017428	1	786.5364	0.000306
	58.76761	39.61623	2.788856	1	905.0404	0.000314
	184.2887	27.95771	3.405659	1	743.4344	0.000353
	207.8778	14.50962	3.153631	0	688.5527	0.00038
DS	244.6455	27.60734	2.589079	1	839.0545	0.000156
	269.001	25.89906	1.701132	1	758.5855	0.000403
	126.915	14.39722	1.657018	0	846.318	0.000453
	270.8095	28.1681	1.496425	1	789.1706	0.00402
	195.7066	33.6045	2.728779	1	975.5855	0.004628
	296.8384	25.96891	2.331379	1	845.2135	0.004756
	200.3242	39.16004	2.578027	1	1126.356	0.005049
	247.9442	38.62538	1.111742	1	825.386	0.005292
	195.1983	12.60131	2.245067	0	1054.5	0.006194
	286.7926	34.11249	1.647067	1	962.9404	0.006812

Table 8. Optimization results when power is maximum 300 (W dm^{-3}) and time is maximum 20 (min)

Algorithm	*Power*	*Time*	*Electrode distance*	*Electrode type*	*Initial Chlorophyll a*	*Final Chlorophyll a*
DE	266.2541	8.643512	1.719983	0	1197.21	0.000003
	121.8393	14.70286	1.427637	0	853.0357	0.000004
	181.7065	11.71665	1.855785	0	848.5507	0.000010
	122.3597	16.40069	1.458446	0	1363.444	0.000011
	88.114	18.34693	2.147467	0	1244.182	0.000025
	191.8063	10.08559	1.072846	0	820.1439	0.000046
	235.4215	9.468854	1.124013	0	1370.725	0.000064
	169.6223	13.08194	1.467117	0	1290.162	0.000078
	128.2034	19.30973	3.312592	0	1332.756	0.000102
	250.1725	7.305586	1.300235	0	818.6908	0.000172
DS	203.4231	12.66206	2.484784	0	905.309	0.000206
	265.8488	11.86848	2.637116	0	1301.496	0.000663
	198.3828	13.58535	2.492489	0	1218.969	0.000918
	266.9814	8.022167	1.99729	0	605.34	0.00106
	273.2927	10.61477	2.54385	0	980.921	0.001385
	276.7541	19.22381	2.508266	1	557.9237	0.001457
	212.4807	11.18528	1.96101	0	1088.547	0.001726
	230.5229	8.928798	1.765343	0	700.5778	0.00223
	299.0072	18.31621	2.265906	1	563.0647	0.004593
	226.3156	10.38376	2.043597	0	902.6361	0.005762

This indicates that, for the considered case study, DS has a tendency to capture different characteristics of the search space and thus locate more variations of the parameters that lead to good solutions.

6. Conclusions

In this work, the performance of two bio-inspired optimizers, DE and DS, was performed and analysed when applied to determine the optimal conditions leading to the minimization of the *chlorophyll a* (as an indicator of algae) from the final effluent of aerated lagoons in a waste treatment plant of Bu-Ali Industrial Estate. The method employed for the removal of *chlorophyll a* is indirect electrolysis and the experiments were performed varying different conditions: retention time, power, type of electrodes (aluminium and stainless steel) and distance between the electrodes.

In order to optimize the process, a model describing the relation between parameters is required. As there are complex mechanisms involved in the electrochemical process and the development of a phenomenological model is difficult, in this work, a two-order regression model was determined. After that, the two algorithms (DE and DS) were applied to determine the conditions for which the highest percent of *chlorophyll a* is removed.

Two distinct cases were considered: i) when no limits on the parameters were imposed (and they vary within the experimental interval) and ii) when limits on some of the parameters were imposed: a) limited power and b) limited power and time.

Using the same settings for number of iterations and population size, a multitude of parameter combinations were identified. In all the optimization cases, both algorithms were able to provide good results. Overall, DS tends to provide slightly worst solution, but had a better capability of providing more combination of parameters leading to acceptable results.

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