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Optimal control of an industrial electrostatic rotating electrode separator using artificial intelligence technics

***Abstract**. The main purpose of this study is the multicriterion optimization in a dynamic context of the operation of an industrial electrostatic separation process with rotating electrode. A study of the operation of this process, performed by using an artificial neural network (ANN), has shown the complexity of adjusting the control variables for use in the industrial field. In this context, a multifactorial control approach has been proposed using meta-heuristics based on artificial intelligence.*

Streszczenie.** W artykule zaprezentowano multikryterialną optymalizację przemysłowego separatora elektrostatycznego z ruchomymi elektrodami. Do optymalizacji wykorzystano sztuczne sieci neuronowe. **Optymalne sterowanie przemysłowym separatorem elektrostatycznym z ruchomymi elektrodami.

Keywords: electrostatic separator; optimization; control; ANN; BBO
Słowa kluczowe: separator elektrostatyczny, optymalizacja, sztuczne sieci neuronowe.

Introduction

The electrostatic technologies with high intensity of electric fields for the recovery of used materials from industrial waste, have in recent years undergone considerable progress [1][2]. However, the necessary adjustment of the parameters of any industrial process to produce the desirable result is a delicate operation. Electrostatic technologies therefore require the implementation of prevention and control strategies for the search of an optimal state in order to improve the quantity and quality of recovered products. [3-6]. Moreover, any experimental and even more industrial process proves to be subject to variations whose origins are multiple : ambient and experimental conditions, natures, compositions, granulometries of waste, resolutions of the parameters of the process, ..., … . These lead to a variability that can be considered as an optimization problem whose resolution is a central topic in operational research.

The main objective of this study is the optimization of the operation of an industrial electrostatic separator, with rotating electrode, designed and realized at the IRECOM laboratory of Sidi Bel Abbes, for different operating regimes.. It involves using methods whose creation was inspired by the analogy with biological phenomena, such as genetic algorithms (GA) neural networks (ANN) [7] [8], or with socio-psychological phenomena such as the ant colony algorithm (ACO) [9] [10] and particulate swarms (PSO) [11] [12]. These methods link two different research areas: operational research and artificial intelligence [13] [14]. Particular interest has been given to the optimization method based on biogeography (BBO: Biogeography-based-optimization)[15]. This young method, inspired by the theory of dynamic equilibrium, is still in its infancy. We begin this article with a general definition of the problem. The construction and implementation of the RNA will be studied and discussed, followed by a presentation of the BBO, Then proceed to an optimization based on it of an industrial process of electrostatic separation. Finally, the BBO will be applied to implement an optimal control strategy of this process, in order to evaluate its robustness compared to some scenarios of disturbances of different natures.

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Problem Definition

The mastery and the control of performance of an electrostatic separation process requires:

- The optimization of the separation,
- Improving the quality of the separated products
- Early detection of malfunctions by monitoring and automatic control of these processes.

The performance of our process (fig.1), operating in continuous mode, can be obtained in two stages:

a) First, we define experimentally optimal profiles for the four variables of interest: the speed of rotation of the rotating cylinder (N), the value of the high voltage applied to the crown electrode (U), the feed rate (D) of the product to be separated and the angular position of the pivot wall (α), which partitions the flow of granules to the collectors..

b) Then we develop a command that takes care of regulating these variables of interest around predefined profiles followed by a disturbance or a dysfunction

Fig.1. Industrial electrostatic Separator with rotating electrode.

The controller proposed in this study (fig.2) uses the measured value of the perturbation to generate the value of the other controllable factors. This solution is applied to the entrance of our installation. It includes in its structure a sample-and-hold device whose role is to discretize the continuous signal and to present the resulting signal as a constant value at the input of the optimization algorithm during a period of the control cycle

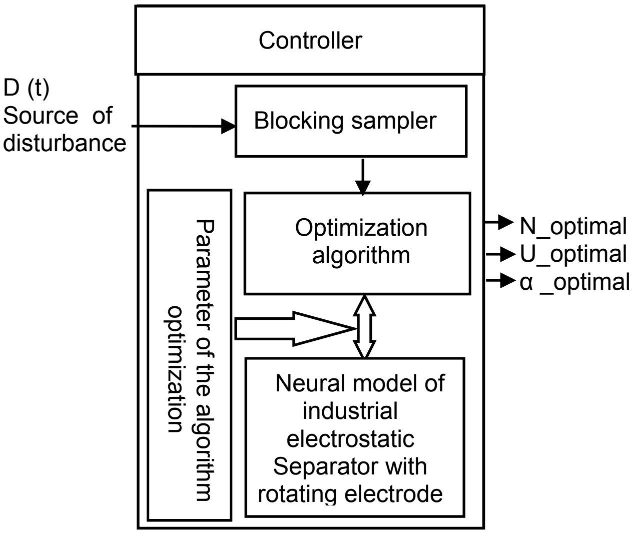

Fig.2. Simplified block diagram of the controller used in the simulation (feed rate disturbance)

To simulate the actual behavior of the electrostatic separator, we take into account the dynamics of each elementary system. The desired value is imposed on the elementary system by our optimization algorithm, which exploits the stationary model of the installation

In practice, the response *y(t)* of the elementary systems of the installation to an echelon-level excitation signal *M* has no oscillation around the final value. This response can be modeled by the equation (1).

$$y(t) = M(1 - e^{-\frac{t}{\tau}}) \tag{1}$$

Where τ is the time constant (the time required of the system response to reach 63% of the desired value)

Figure 3 shows the model diagram used in the simulation of the recovery of the insulating, mixed and conductive product

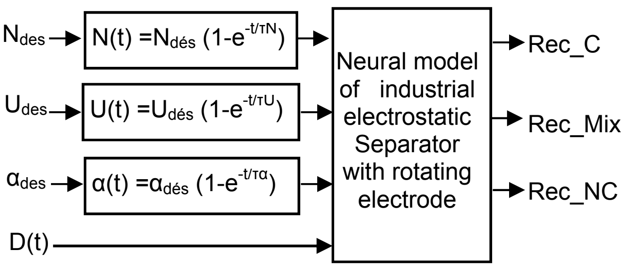

Fig.3. Simplified block diagram of the electrostatic separator model used in the simulation

ANN modeling and implementation

The control of the functioning of the electrostatic separator is done by simulation on a non-linear model of the recovery of the conductive (Rec_C), non-conductive (Rec_NC) and mixed products (Rec_Mix), developed by the artificial neural network that are inspired by the structure of biological nervous systems

This model predicts the value of the recovery of these three products depending on rotation of the rotating cylinder (N); the value of the high voltage applied to the corona electrode (U), the feed rate (D) of the product to be separated and the angular position of the pivoting wall (α).

There are currently more than 50 types of networks used in different applications [15][16]. In the present work, we are particularly interested in feed-forward networks. Figure 4 illustrates the structure of this network

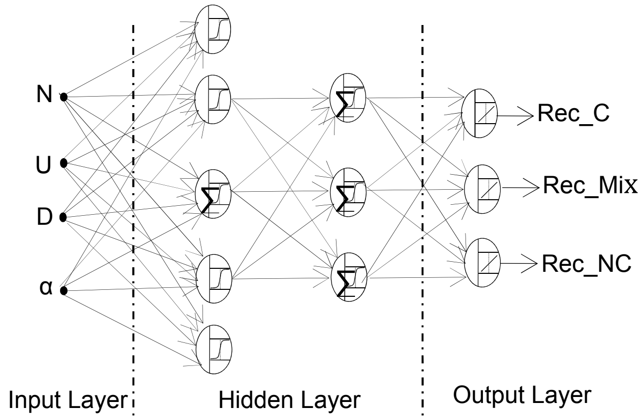

Fig.4. Feed-forward artificial neural network

A learning phase is needed to determine the weights of connections within the network so that the network is able to identify the links between the responses and the factors of the studied installation. In our study, we applied a standard backpropagation algorithm to perform the learning operation. This type of algorithm uses the gradient method as an optimization method to update the weights of connections within the network.

A digital database is generally used which gathers information on the operation of the system to be modeled in a well-defined study area. It must include three subsets: The learning base, by which the estimation of the model parameters is carried out, generally represents 65% of the totality of the experiments carried out. The remaining 35% of the experiments are used as a basis for testing and validation, on which the ability of the network to recognize untrained examples is tested. This last operation must therefore make it possible to estimate the generalization capacity of the established network, which is the determining criterion for this type of model.

The boundaries of the experimental domain are grouped in Table 1

Table 1. Validity of established models

Factor	N [Rev/min]	U [kV]	D[g/min]	α [°]
Minimum value	60	20	4800	-10
Minimum value	90	24	7200	10

The best performance of the ANN architecture is determined by the lowest mean squared error (MSE) and the maximum coefficient of determination (R-squared) that defines the fit integrity of experimental data [17].

$$MSE = \frac{\sum_{i=1}^{n}(T_i - Y_i)^2}{n} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(T_i - Y_i)^2}{\sum_{i=1}^{n}(Y_i)^2} \tag{3}$$

where T is target value and Y is output value.

Figure 5 show the performance of our neural network. The X-axis represents the measured values (Y_measured) and the Y axis represents the predictions (Y_predite). The line of the bisector indicates the equality between measured values and predicted values. All values are normalized between -1 and 1. We can note that:

- The points are positioned around this bisector in a fairly wide range of values
- The coefficient of determination R^2 close to 1: 0.99982
- The mean squared error, MSE close to $4.051.10^{-3}$ (Fig. 6).

This indicates a good prediction for separation performance using ANN.

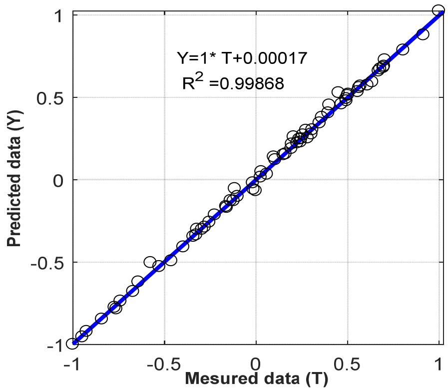

Fig.5. Neural network performance: R-squared between target value and predicted value

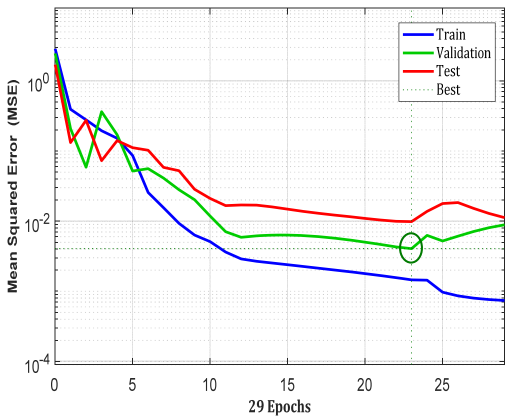

Fig.6. Neural network performance: MSE between training, validation and testing;

The proposed algorithm based on biogeography BBO

Biogeography-Based Optimization. BBO is a newly invented heuristic algorithm that was first introduced in 2008 [18]. Like GAs or PSOs, The BBO algorithm manipulates a population of individuals called islands or habitats. Each island represents a possible solution to the problem that should be solved. Its Habitat Suitability Index (HSI), a measure of the quality of a candidate solution, determines the fitness of each island and each island is represented by SIVs (Suitability Index Variables)[19] . The two main operators that have governed its operation are migration and mutation.

A good solution to the optimization problem, like that of electrostatic separation, is an island with a large number of species, which corresponds to an island with a large HSI.

Table 1 represents and redefines the terms and scope of BBO on our optimization problem. However, since GA is considered the most popular algorithm in this class of optimization methods, Table 1 compares these characteristics with those of BBO. The comparison of the performance of these two algorithms is also considered, which helps to understand the BBO much more explicitly [20].

Table 2. Definitions and concepts of the BBOvs definitions and concepts of GA

BBO	GA
1- Population	Population
2- Habitat (individual)	Chromosome (individual)
3- HSI	Fitness
4- SIV	Gene
5- Mutation	Mutation
6- migration operator	Crossover operator
7- A good solution is characterized by a large HSI	A good solution is characterized by a great fitness

The BBO algorithm begins with a finite number of individuals selected by a uniform firing process in the research space forming the initial population. After evaluation of the initial population, some individuals are selected to participate in the migration operation that creates a new set of individuals. The descendants will be mutated in turn. The fixed mutation rate of the proportion of the population that will be renewed each generation. Finally, a replacement phase consists of replacing the parents with the new descendants, in order to have a new population, of the same size as at the beginning of the iteration. The algorithm ends after a number of generations.

Results

The control of the functioning of the electrostatic separator is done by simulation on a ANN model of the recovery of the conductive (Rec_C), non-conductive (Rec_NC) and mixed products (Rec_Mix), developed by the design of experiments methodology. This model predicts the value of the recovery of these three products depending on rotation of the rotating cylinder (N); the value of the high voltage applied to the corona electrode (U), the feed rate (D) of the product to be separated and the angular position of the pivoting wall (α).

➢ ***Simulation of the model in continuons mode***

In this section, we present the numerical results of the multi-objective optimization obtained by our BBO algorithm, The criterion adopted for the optimization of the separation process is the following: simultaneous maximization of conductive and non-conductive product recovery, and minimization of mixed product recovery

The solutions of this multi-objective optimization problem must respect the constraints, i.e. the lower and higher limits imposed for each factor.

The mathematical expression of the problem can be represented by the following equation system:

$$\begin{aligned} &\text{Max } [Rec\_C\ (N, U, D, \alpha)] \\ &\text{Max } [Rec\_NC\ (N, U, D, \alpha)] \\ &\text{Min } [Rec\_Mix\ (N, U, D, \alpha)] \\ &(N, U, D, \alpha) \in \grave{\Omega} \end{aligned} \tag{4}$$

With `Ω, being the domain of possible solutions defined in table 1.

The multi-objective approach based on the aggregation of functions has been used to improve the quality of the electrostatic separation of granular mixtures by our industrial device. This approach consists in transforming the multi-objective problem into a single objective problem, by assigning to each objective function an importance factor that is considered as a measure of the contribution of each of these functions in the multi-objective system. Its advantage is to produce a compromise solution, which does not require the intervention of an expert for the choice of the final solution.

For this work, we experimented with combinations of several criteria. At the end of the numerous tests carried out and the results obtained, we have selected the one that gives each function a weight equal to one third, in order to guarantee a maximum recovery with a high purity.

The BBO algorithm was used in its basic configuration proposed by its author [18] whose parameters are reported in Table 3.

Table 3. Parameters of the BBO algorithm

Parameters	Notation	Values
Population size	NP	100
Probability of mutation	pm	0,01
Size of the elite memory	nelit	2
Maximum immigration rate	I	1
Maximum emigration rate	E	1
Maximum number of generation	gmax	100

Note that all these algorithms have been programmed and executed under Matlab R2016b , with a PC of 4Go RAM, 2.30-GHz CPU.

Figure 7 and 8 respectively illustrate the optimal evolution of the controllable factors and the Evolution of optimal product recovery during multi-objective optimization by the BBO algorithm:

Table 4 shows the configuration of the best individual determined by our optimization algorithm

Table 4. Optimal parameters configuration of our separator using BBO algorithm

Factor	Controlled factor			
	N[Rev/min]	U[kV]	D[g/min]	α [°]
Optimal values	89,98	23,98	4781	-10
Factor	Product recovery			
	Rec_C [g]	Rec_Mix [g]	Rec_NC [g]	CPU [s]
Optimal values	728.41	1348.14	1903.47	0.128

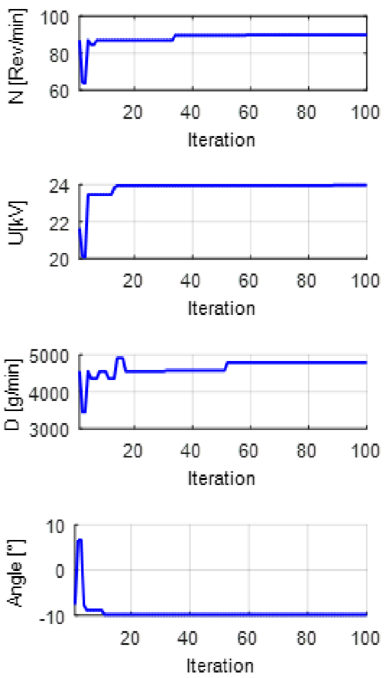

Fig.7. Optimal evolution of the controllable factors

➢ **Model simulation in disturbed regime:**

In order to evaluate the impact of a disturbance on the electrostatic separation process and to test the efficiency of the algorithm developed, a comparison between two processes was performed. The first of these processes is controlled by BBO optimization algorithm, the second is an uncontrolled process, whose initial state of the system is characterized by the optimal values previously determined. Also two scenarios with single or double disturbances are they proposed.

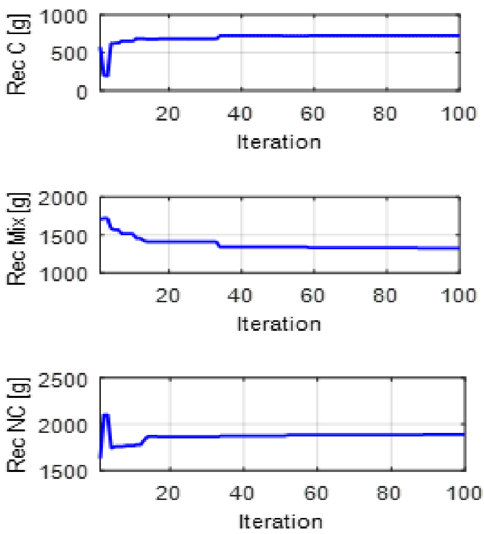

Fig 8. Evolution of optimal product recovery during multi-objective optimization

- Scenario1: Disturbance of the rotation speed of the drum: Figure 9 represents the simulation of the case of a reduction of the rotation speed of the drum of our electrostatic separator; this variation in speed has led to a significant reduction in the recovery of the conductive product from 728,41 g to 246.2 g. This can be explained by the fact that the conductive particles do not detach sufficiently enough from the surface of the rotating electrode to land in their reserved compartment. The centrifugal force applied to the particle has decreased. This also explains the increase in the mixed product recovery mass since the product of the separation is not arranged in the monolayer form, which does not create the conditions of change of sign for all the particles

On the other hand, the response to this disturbance of our controller for the regulation of our electrostatic separation process made it possible to increase by 17.6 % the recovery of the insulating product to 2239 g. The purity of recovery was also adjusted by reducing the amount of the mixed product by more than 231 g. We record a better performance of the process controlled by the BBO algorithm.

- Scenario 2: disturbances of high voltage and rotational speed: Scenario 2 is a double disturbance that impacts both the high voltage and the rotational speed of the drum. This type of situation can be caused by an anomaly in the feed of the separator. The responses to this disturbance of controllers of controlled and uncontrolled processes are shown in Figure 10. This incident will degrade the recovery in two compartments. For the conductive product for example, the recovery, which should exceed 700 g, will increase to 81.2 g, while the mixed product, will exceed the 1963 g instead of 1348.17 g. The regulation controlled by the BBO algorithm made it possible to minimize the mixed product at 1506 g, a decrease of 33.9% compared to the value obtained before the disturbance. The recovery of the conductive product was also increased by more than 170 g. Although the values are close between the two situations. The difference cannot be neglected under the conditions of an industrial application. Note also the evolution of the insulation product, which despite not being affected by this incident recorded an increase of more than 339 grams from the initial state.

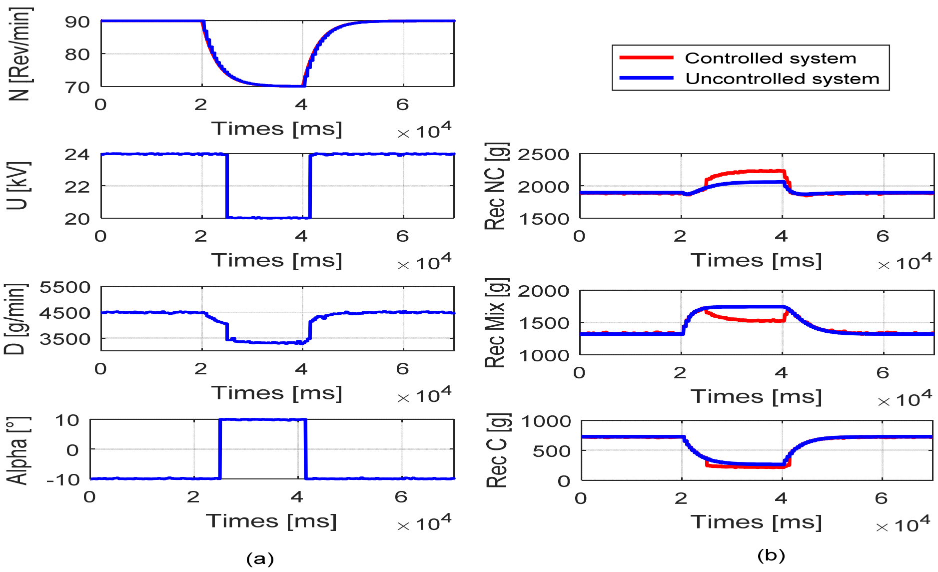

Fig.9. Regulation of the electrostatic separation process by the BBO algorithm - Scenario 1 : (a) Evolution of the controllable factors (b) Evolution of the electrostatic separator recovery

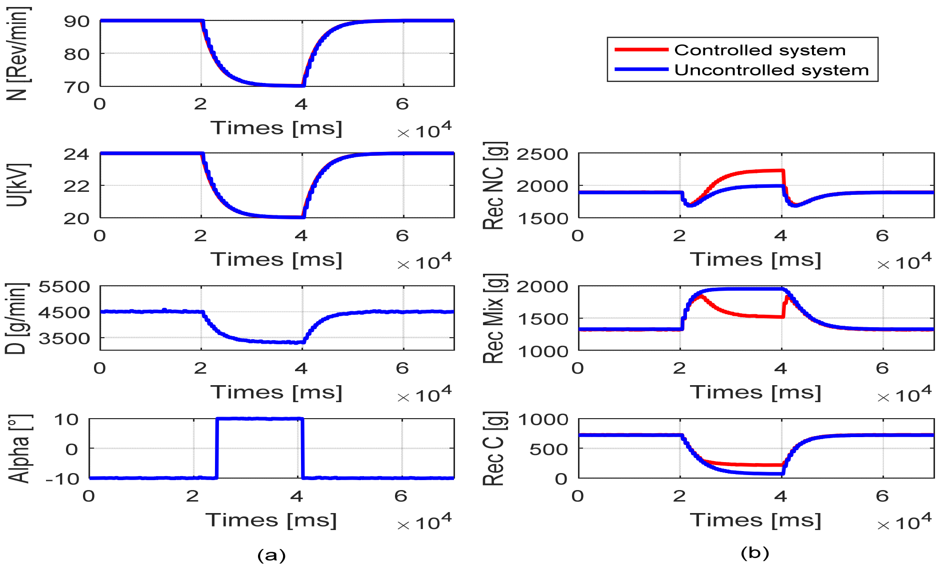

Fig.10. Regulation of the electrostatic separation process by the BBO algorithm - Scenario 2 : (a) Evolution of the controllable factors (b) Evolution of the electrostatic separator recovery

In the table below, we summarize the optimal values of the various parameters, following the reaction of our controller to a disturbance in the two scenarios

Table 5. Summary of the results of regulation

Scenario 1							
Parameters	N [Rev/min]	U [kV]	D [g/min]	α [°]	Rec_C [g]	Rec_Mix [g]	Rec_NC [g]
Optimal values	89.98	23.98	4781	- 10	728,4	1348.17	1903.52
without regulation	75	23.98	4781	- 10	246.2	1752,02	2019.38
with regulation	75	20	3417	10	228.2	1520.4	2239
Scenario 2							
Parameters	N [Rev/min]	U [kV]	D [g/min]	α [°]	Rec_C [g]	Rec_Mix [g]	Rec_NC [g]
Optimal values	89.98	23.98	4781	- 10	728,4	1348.17	1903.52
without regulation	70	20	4781	- 10	81.2	1963.54	1979.11
with regulation	70	20	3458	10	251. 8	1506.25	2242.63

Conclusion

The Operators of industrial processes for the electrostatic separation of granular mixtures are forced to find fast and effective solutions to control the impact of disturbances that could affect the proper functioning of their processes. The quality and quantity of recycled products can be rapidly deteriorate if evolutionary technics are not implemented to optimize the performance of these installation Since electrostatic separation is a multifactorial process, it has been verified that the use of artificial neural networks could be very beneficial. The study carried out, showed that this technique remains a powerful and efficient tool for the mathematical modeling of these processes.

A multifactorial control approach of an industrial separator that relies on the use of optimization methods based on artificial intelligence is proposed in this article. An algorithm based on biogeography (BBO) has been implanted in the electrostatic separation process. The latter has caught our attention for his performance;

To test the BBO optimization, two representative scenarios of disturbances likely to occur in an industrial environment were simulated. These are disturbances of the rotation speed alone or in combination with that of the high voltage. This situation is characteristic of a disturbance caused by an instability or a drop in the power of the electricity network. RNA-BBO-controlled regulation has proved even more effective by significantly minimizing the impacts of these disturbances

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