A Novel Approach to Address Process Plant Layout based on a Bacterial Genetic Optimization Algorithm

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Abstract. The process plant layout is a determining factor for the efficient and secure operation of it. In this sense, define the best position of each process unit contributes to reducing transport costs and the explosion and fire risk. This issue has been addressed in the past by different methods like expert criteria, simulation, and optimization. In this contribution, a hybrid bacterial genetic optimization algorithm for process plant layout is introduced, which solves a mathematical model that minimize interconnection cost and land cost. In addition, the model takes into consideration facilities dimensions, minimal distances among facilities, and minimum distance up to the property boundary. The performance evaluation was carried out with a case of study of literature, and the results expose the advantages of this proposal in performance and time.

Keywords: Process plant layout · Bacterial optimization algorithm · Genetic Algorithms · Metaheuristics · Chemical Engineering

1 Introduction

The optimal design of processes plants layouts is one of the main issues in chemical engineering, which is in continuous development as is described by Xu and Papageorgiou [7], which expose different approaches to address this problem. Despite the advances in the computational matter, to achieve that all the design factors converge in a single model is impossible, and the same process variables are not used in all cases. Among the most used factors are the economic, operability and flexibility, availability for future extensions, security and reliability, and finally the environmental.

Plant design is a crucial step for a new production plant; but in some cases during the design process, some risks are dismissed, due to the need to produce more efficiently. However, to minimize the risks and possible emergencies has been more relevant because they represent a more significant amount of costs for lawsuits or infractions to the norms.

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Therefore, companies must evaluate the location and distribution of the plant meticulously, because they must know in detail about what, how? With what? Also, where? Provide their services, together with the details of the capacity to achieve the best functioning of the facilities [5].

Poor distribution of spaces in the plant leads to problems such as hampering areas necessary for movements, harming workers or staff in the vicinity, or limited storage space. These because many facility designs lead to solutions that not admit modifications in areas, forms, or orientation, for which in their design do not take into account passages or interior walls.

Regarding production process, the excellent management of spaces is essential, because it contains high-risk phases, where if the equipment is close to places where workers are located, it can cause fatal damage and even death, either by the uncontrolled reaction, pressure leaks or by inhalation of toxic reagents during production.

Having said the above, the main interest in the realization of this work is to define the best position of a set of facilities in a process plant by mean of a hybrid metaheuristic algorithm based on artificial bacteria and sexual reproduction of Genetic Algorithms in the solution of study case from [4].

2 Theoretical framework

In the design of process plants, it is essential, the definition of the location of each equipment into the plant. Due to it is the starting point to optimize each of the sub-processes that make up the production plant. That is why these problems, make up a disjunctive to which every organization faces, in which it is necessary to define the allocation of the equipment or process and the required connections among these. In this sense, a high number of different approaches have been presented. The initial approximations were based on the heuristics, just as it did [10] where they performed a solution without guaranteeing that it is the most optimal. R. Jayakumar [2] proposed the location of units by sections and defines that there are three methods of developing these problems, the exact plans, heuristics, and meta-heuristics; depending on the mathematical model formulation which fits the conditions that the study case needs [11].

In this way, heuristic meta-models began to appear, in which it is possible to recover or take into consideration previous models. An approach applied to the styrene industry is shown in [1], in which genetic algorithms are implemented and gave an effective strategy to find excellent and practical solutions for a design problem, although it did not guarantee to find the global optimum.

Thanks to the above meta-heuristic approaches, which are the first approach in the hybridization of heuristics for the resolution of combinatorial problems [6], allowing to arrive at the non-linear programming of mixed integers, as the model proposed by Penteado and Ciric [9], where financial risks related to accidents and spreading to neighboring units are taken into account for the first time, as well as other terms such as pipes, land and the costs of protective devices.

Once entered into the non-linear programming of mixed integers, we continue with the mathematical models which were presented by Papageorgiou and Rotstein [7]; where the optimal location and orientation for each equipment is determined, and simultaneously the performance criterion given in the design is minimized, this model was generalized to take into account the design organization of the process plant in the production sections.

Due to the multiple configurations of different plants, it is necessary to take into consideration the study options carried out by Suzuki [10] which are the assignment of equipment to different floors, that is, not to use a plant along only, but multiple levels plant, which satisfies preferential number of equipment and also takes into account vertical pumping and land costs.

That said, [8] presents a mathematical model where it considers the problem through the design of multiple floors, which determines the number of levels, the necessary land, the location of equipment and the optimal amount of equipment per floor simultaneously, this in order to minimize total costs in the design of the plant, this presents the formulation of the mathematical model, while demonstrating its applicability to the demonstration in the non-linear model, this document has been defined as fundamental basis for the generation of the mathematical model presented by Jung [3]. In which explores the available methods for the design of chemical plants with better and safer designs, where he incorporates the security process and with QRA approaches within the models used to solve the problems of plant designs, where they managed to overcome some of the difficulties associated with non-linearity, uncertainties, and precision for modeling consequences.

3 Mathematical model

The mathematical model defined for this contribution takes into consideration the study case formulated by Jung et al., [4]. The model minimizes the land cost and the interconnection cost equation 1, and it is subjected to three constraints, which are described in equations 2 to 4. Equation 2 guarantees that the distance $d(i,j)$ between the facilities centers be more than the minimum allowed $dmin(i,j)$, using Euclidean distance. Equations 3 and 4 guarantees that the facilities' borders being separated higher than $dminf(i)$, the minimal distance from the property boundary to the facility. Equations 5 to 7 defines how to calculate the land cost. Equation 8 defines the interconnection cost and finally, equation 9 establish how is calculated $dmin(i,j)$. The model is shown as follow:

Minimize:

$$Z = LC + IC \tag{1}$$

Subject to:

$$d(i,j) \geq dmin(i,j) \tag{2}$$

$$x(i) \geq \frac{Lx(i)}{2} + dminf(i) \tag{3}$$

$$y(i) \geq \frac{Ly(i)}{2} + dminf(i) \tag{4}$$

Where:

Land cost (LC):

$$X_{size} = max\left[x(i) + \frac{Lx(i)}{2} + dminf(i)\right] \tag{5}$$

$$Y_{size} = max\left[y(i) + \frac{Ly(i)}{2} + dminf(i)\right] \tag{6}$$

$$LC = UL * X_{size} * Y_{size} \tag{7}$$

Interconection cost (IC):

$$IC = \sum_{i=1}^{m}\sum_{j=i}^{m} UIC(i,j) * d(i,j) \tag{8}$$

i, j : Facilities index; $i = 1, \ldots, m$ and $j = 1, \ldots, m$
m : Number of facilities.
$d(i, j)$: Euclidean distance between centers of facilities i and j.
$dmin(i, j)$: Minimal distance between centers of facilities i and j.
$dminf(i)$: Minimal distance from the Property Boundary to facility i.

$$\begin{aligned} dmin(i,j) = & \sqrt{\left(\frac{Lx(i)}{2}\right)^2 + \left(\frac{Lx(j)}{2}\right)^2} \\ & + \sqrt{\left(\frac{Ly(i)}{2}\right)^2 + \left(\frac{Ly(j)}{2}\right)^2} \\ & + mindisb(i,j) \end{aligned} \tag{9}$$

$mindisb(i, j)$: Minimal distance between the borders of facilities i and j.

Table 1: Data for study case [4]

Facility (i)	***type of facility***	***Lx-Ly [m:m]***	$dminf(i)$ ***[m]***
1	control room (nonpressurized)	10-10	30
2	administrative building	20-15	8
3	warehouse	5-10	8
4	high pressure storage sphere	10-10	30
5	atmospheric flammable liquid storage tank 1	4-4	30

Table 1: Data for study case [4]

Facility (i)	***type of facility***	***Lx-Ly [m:m]***	$dminf(i)$ ***[m]***
6	atmospheric flammable liquid storage tank 2	4-4	30
7	cooling tower	20-10	30
8	process unit	30-40	30

Table 2. Unit interconnection cost, $UIC(i, j)$ [4]

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1		0,1	0,1	10	10	10	10	10
2	0,1		0,1	0	0	0	0	0
3	0,1	0,1		0,1	0,1	0,1	0,1	0,1
4	10	0	0,1		0,1	0,1	100	0
5	10	0	0,1	0,1		0,1	100	0
6	10	0	0,1	0,1	0,1		100	0
7	10	0	0,1	100	100	100		100
8	10	0	0,1	0	0	0	100	

Table 3. Minimal distance between the borders of facilities i and j, $mindisb(i, j)$ [4]

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1		5	5	30	60	60	30	30
2	5		5	60	60	60	30	60
3	5	5		60	60	60	30	60
4	30	60	60		10	10	30	15
5	60	60	60	10		4	30	5
6	60	60	60	10	4		30	5
7	30	30	30	30	30	30		30
8	30	60	60	15	5	5	30	

Tables 1 to 3 provides the study case data which was used in this work.

4 Bacterial Genetic Optimization Algorithm for Process Plant Layout BGOA-PPL

In this proposal, a bacterial genetic optimization algorithm is introduced to address the process plant layout problem; bacterial algorithms model food-seeking and reproductive behavior of common bacteria such as E. Coli as an optimization process. Meanwhile, Genetic Algorithms simulate sexual reproduction as an optimization process. In this sense, BGOA-PPL exploits exploration advantages of bacterial algorithm and convergence of Genetic Algorithms to define process plant layout.

The process starts randomly generating the initial bacteria population, next objective function evaluation, chemotaxis process, sexual reproduction, and elimination and dispersion. The loop continues repeating the sequence from objective function evaluation up to fulfill the stop criteria, as is described in the algorithm 1.

Algorithm 1 BGOA-PPL

```
Generation of initial bacteria
for i = 1 to Max generation do
    Objective function evaluation
    Chemotaxis
    Sexual Reproduction
    Elimination and Dispersion
end for
```

Where:
i population index.
j chemotaxis index.
θ: is the bacteria population.
S: is the number of individuals of θ or the size of bacteria population.
$J(\theta^i)$: is the value of objective function of θ^i.
p^i_{ed}: is a random number to realize the elimination and dispersion of θ^i.
P_{ed}: is the probability of elimination and dispersion.

BGOAPPL seek optimum value through the bacteria chemotaxis and share information through sexual reproduction, and the elimination-dispersion process has been defined to avoiding falling into premature convergence by a locally optimal, creating new bacteria dispersed or located in other positions different to the originals which replaced.

4.1 Chemotaxis

This process simulates the movement of an E. Coli cell through swimming and tumbling via flagella. Chemotaxis, explore search space in two stages. Firstly tumbling, where randomly is defined the direction of a unitary vector which represents a trace of a source of food. The second stage is swimming, where each bacterium goes forward in the direction the unitary vector previously defined. Suppose θ^i represents $i-th$ bacterium at $j-th$ chemotactic, $k-th$ reproductive and $l-th$ elimination-dispersal step. $C(i)$ is the size of the step taken in the random direction specified by the tumble. Then in computational chemotaxis, the movement of the bacterium may be represented by:

$$\theta^{i}\left(j+1\right)=\theta^{i}\left(j\right)+C(i)\frac{\Delta(i)}{\sqrt{(\Delta^{T}(i)\Delta(i))}} \tag{10}$$

Where $\Delta(i)$ indicates a vector in the random direction whose elements lie in $[-1, 1]$.

4.2 Sexual Reproduction

Sexual reproduction includes parent selection and cross-process, firstly define an elite or the best-fitted individuals of the population (the user establishes the group size). Next, a selection process is carried out, including the elite as part of parents and other individuals who are selected by the binary tournament. In which, two individuals are randomly selected, and their objective function values are compared, the tournament is won by the individual with a better amount of the objective function.

Secondly, the group of parents is crossed to generate children or new individuals, which take features of their parents. The cross-process is carried out in two ways; the first option is by exchanging parents segments with a simple cross point to generate children. The second is making the new individual by a weighted average of the parents.

4.3 Elimination and Dispersion

In the evolutionary process, elimination events can occur such that the bacteria die by adverse conditions. In this context, bacteria to avoid their extinction, randomly disperse into a new environment using some influence, like an organism, which transports bacteria to other locations or bodies where exist better conditions to survive. This process has the effect of assisting in chemotaxis, since dispersal may place bacteria near of suitable food sources and avoid in this way local optimums. From the evolutionary point of view, elimination and dispersal are used to guarantees the diversity of population and to strengthen the ability of global optimization.

In BGOA-PPL, bacteria are eliminated with a probability of less than Ped (probability of elimination and dispersion). To keep a constant bacteria population, if a bacterium is removed, this is replaced by others in a random location on the optimization domain.

4.4 Constraints handling

The constraint handling process was made by mean of two strategies. Firstly penalization was applied to unfeasible solutions, in parallel, the second strategy was implemented, in it if the equation two is not satisfied, the two facilities are separated up to satisfying equation 2. The combination of the two strategies provides feasible solutions and reduce the time to convergence.

5 Results

The performance evaluation was carried out running the proposed algorithm in the solution of the study case [4] and solving the mathematical model in GAMS using DICOPT solver, the best solutions achieved with BGOA-PPL and GAMS are shown in Table 4, in which it is possible to appreciate how BGOA-PPL achieve a better solution in terms of objective function. Although, the area in greater in BGOA-PPL, a less interconnection cost produces a reduced in the total cost in contrast to the GAMS solution. The coordinates of the best solutions with the two methods are summarized in Table 5, meanwhile in Fig.1, a plot of BGOA-PPL solution as a schematic layout.

Table 4. Results of GAMS and BGOA-PPL

	GAMS	***BGOA-PPL***
Area [m]	19147,5	20128
IC [U$]	34648,1	25685,05
LC [U$]	95737,8	100640
Total Cost Z [U$]	130386	126325,05

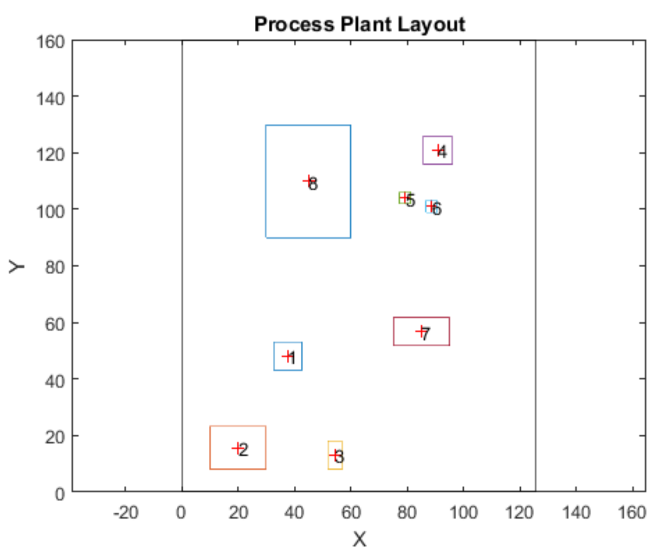

Fig. 1. Layout of the best solution of BGOAPPL.

Table 5. Best solutions with GAMS and BGOA-PPL

GAMS		**BGOA-PPL**	
X	***Y***	***X***	***Y***
35,48	40,05	37,58	48,05
33,45	15,50	19,96	15,50
10,50	13,00	54,32	13,00
35,00	95,06	90,85	120,52
41,62	113,82	79,20	104,34
49,68	108,49	88,60	100,59
83,47	35,00	85,06	56,71
81,67	101,16	45,00	109,82

In terms of the proposed algorithm performance, Fig.2 exposes in box-plots graphs the distribution of the BGOA-PPL solutions in values of the objective function and the time spent to achieve each one of them. As is possible, appreciate Fig.2 a) shows an algorithm that could provide a set of feasible sub-optimal solutions that will be used as a seed to achieve the optimal solution in subsequent processes. Besides, the time spent (Fig.2 b)) in achieving this set of solutions is low in the scale of the process plant design project which is a significant advantage to develop a process with a growing improving up to the final version.

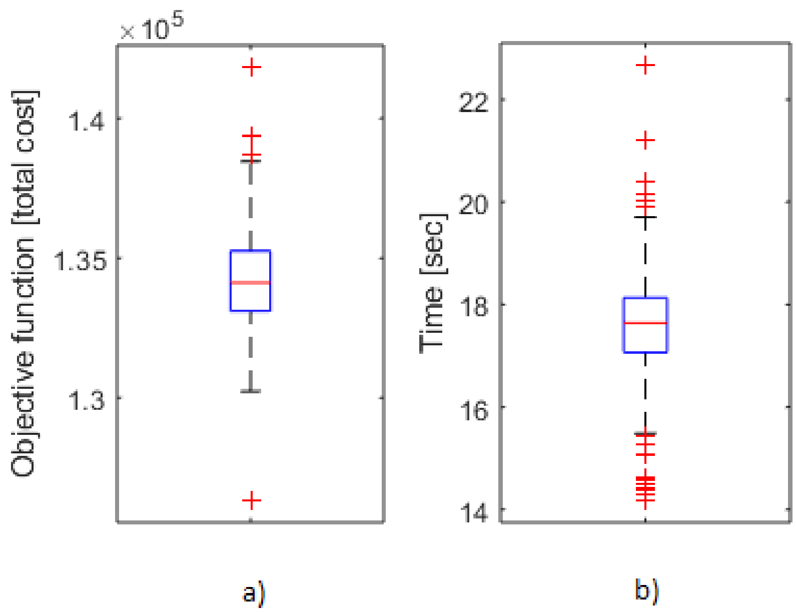

Fig. 2. Boxplots of objective function (a) and time (b) spent in the solution of study case.

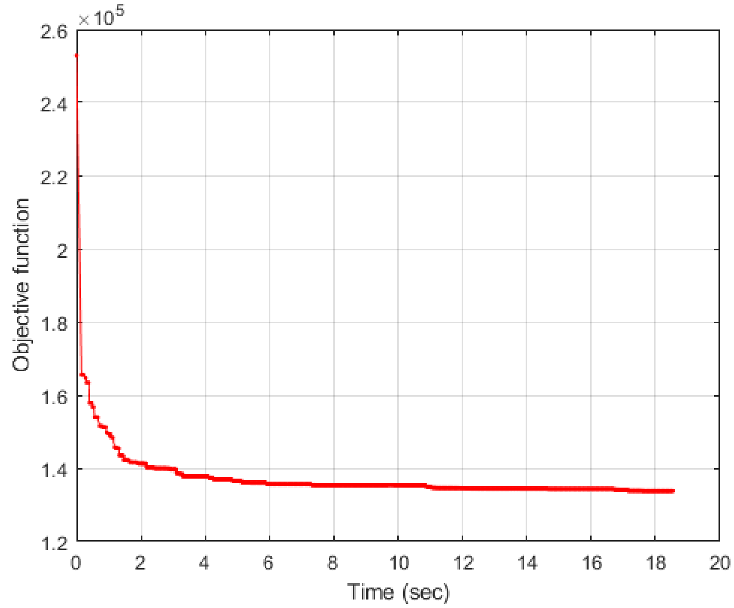

Fig. 3. Example of BGOA-PPL run

Finally, Fig.3 exposes a decreasing graph in which the combination of the different operators implemented in BGOA-PPL works to find a better solution in each iteration up to complete the maximum number of iterations or generations in a reduced time, near to 18 seconds.

6 Discussion

The results presented above suggest that the proposed method is a viable option for the solution of design problems such as the study case, in addition to taking into account all variables such as minimum distances and regulatory standards for its implementation. The proposed method allows seeing multiple options concerning the reduced time spent and the number of iterations, in comparison with others that can only show a viable option and take a little longer to stabilize the response. Finally, the results are comparable with other works, in which other meta-heuristics or non-linear methods are applied to solve such problems.

6.1 Conclusions

The proposed hybrid algorithm based on Bacterial and Genetic algorithms to address the process plant layout, shows promising results to face this mixed-integer nonlinearly constrained optimization problem and other kinds of issues in chemical engineering.

The lowest time spent running BGOA-PPL is an advantage, due to allows us to generate a significant number of feasible solutions that provide different alternatives that expand the horizon of the designers' team. Therefore, it is possible to achieve more robust designs, reducing cost and increasing the performance of the plant operation.

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