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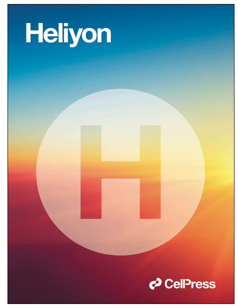

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Shipyard Facility Layout Optimization through the implementation of a Sequential Structure of Algorithms

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ABSTRACT

The objective of this work is to optimize a shipyard facility layout through required departments' closeness conditions to minimize total material handling cost. In order to resolve this type facility layout problem, departments' closeness conditions must be respected when the manufacturing and material handling processes require it according to the supply and movement requirements throughout production flow, especially when the activity requires material handling equipment of common use between departments. As a result of this work the optimization is achieved through the implementation of a stochastic sequential algorithm, comprising the following steps: 1) Topological Optimization from a Genetic Algorithm, 2) Transferring the centroid coordinates of each department from the topological grid to the geometrical grid from a computational procedure, and 3) Geometrical Optimization from a Stochastic Growth Algorithm, with a fine-tuning of the solution achieved using the Electre Method and a Local Search Method. Computational experiments were performed to prove the effectiveness of the system and evaluate the performance of each algorithm listed in the scope of the proposed solution. We have proved that the proposed Sequential Structure of Algorithms can successfully solve the problem. Computational experiments results are also presented in the supplementary material of this work.

KEYWORDS

Evolutionary Computation; Facility Layout Problem; Genetic Operators; Stochastic Growth Algorithm; Electre Method and Local Search Method.

1. Introduction

Facility Layout Planning (FLP) is one of the most important classic operations management and industrial engineering problems. In the Production Environment Engineer to Order (ETO), more specifically for shipyards, the material handling represents one of the global shipbuilding challenges due to the time required for loading, moving, and unloading material in and between different areas of the industry, which explains why the material handling costs usually represent the largest share of the production costs considered in FLP. In this case, it stresses the importance of the attention given to the departments' closeness conditions due to the fact that they reduce the material handling costs on the production system while ensuring a highly connected and efficient workflow.

ETO production systems contemplates certain operational specifics which raise the complexity material flow and consequently the production flow synchronism, as well as exercise great influence on the Total Material Handling Cost (TMHC) as mentioned.

In these cases the FLP has as its main objective to project the material flow in order to reach high productivity in function of efficiency of fabrication processes and of reducing the TMHC. With respect to synchronism, this depends on the product's project complexity, the facility layout project, the production planning, the number of projects being fabricated at the same time and the balancing of workload by department based on the product's flow matrix [1–5].

Considered an ETO production environment, the factory floor of a shipyard has related specificities which require equipment for material handling with high load lifting and displacement capacity, in order to maintain the synchronism between transformation processes.

Among the main related specificities, especially in the case of the shipbuilding industry should be highlighted:

(1) Production with a wide range of production orders per project being manufactured at the same time, which increases the dispute for the same manufacturing and material handling resources during the operation;

(2) Projects with high customization level and material structure of several levels with assemblies of complex geometry; and

(3) Assemblies and sub-assemblies with different constructive types containing structural components with amplified dimensions of heavy steel materials moved by the factory after being processed in each step of the shipyard's production flow until the pre-building department [2, 6].

Based on what was foregoing, the research gaps which motivated the authors of this work by development the optimization process based on the implementation of a sequential structure of algorithms there were two, as described below.

Research gap (RG1): However, even with all this complexity, we identified in the literature that in the shipbuilding sector the shipyard facility layout problem, in the large majority of cases, has been solved without the imposition of a systematic design process, with only a few studies on these simulation and optimization approaches for designing a shipyard layout that meets all design requirements have been explored up to the present. See [2, 5, 7–10, 11, 12].

Research gap (RG2): From the point of view of an in-depth quantitative analysis, as part the scope of the systematic design process, approaches for layout evaluation through the non-linear mathematical optimization models should be considered as paramount, once the FLP is a non-polynomial hard (NP-hard) optimization problem. In this case, it is difficult or impossible to obtain a global optimal layout or satisfactory layout in reasonable time. See [2, 12, 13].

In the work of [12] are related 120 works using meta-heuristics to find suboptimum solutions to FLP, which collectively corresponded to about 80% of the research problem studied cases when we consider other approaches, both qualitative and quantitative. Of the 120 works in [12], 53 are among those who used genetic algorithms and 33 are among those who used simulated annealing algorithms; both algorithms classified as Model-Based Stochastic Search Methods. In terms of performance and result, in the vast majority of cases of the FLP, the GA excels in relation to the SA.

[14] point out, for example, that the results obtained with the application of these methods to solve variations of the floor-plan layout problem of the slicing tree show that GA minimizes total cost from 1.7% to 9.8% compared to the SA within the same computational time. Beyond the best performance, the choice of using the GA in the 1st stage in the case of this work is due to the fact that one of the preponderant features of GA is that it creates or changes a number of potentially viable solutions simultaneously, unlike the deterministic approach, designed to improve a single solution at each iteration of a simulation.

The simultaneous modification of a set of solutions allows greater robustness at the “layout optimization” process, which significantly increases the opportunities to achieve the global optimal solution avoiding the search process falling into a local optimum [14]. The simulated annealing method does not explore full potential from the solution space considered for each of the subsequent iterations of optimization and, consequently, useful information about the function surface that can be inferred on known solutions in order to improve the solution current is not considered [15].

It is noteworthy, though, that GAs come in various forms and types and the best technique varies due to each problem and its characteristics. This work evidences that, achieving better results through the application of a different GA type from the original work for the 1st stage problem.

In the 2nd stage, as to the operability of the stochastic–growth–based loop with the implementation of the SGAELS, we prove from the results achieved, that the algorithm presented in a "robust and effective" performance during building of outline of the each departments´ area, respecting the material handling flow according to departments' closeness conditions, defined conditions after technical evaluation by the project team.

The fitness function is a quantitative criterion that leads an optimization process with repeatability and reproducibility assured, to the extent that constraints were properly established based on the best practices of design. This work evidences that, with the implementation of the SGAELS, achieving better results from the original work for the 2nd stage problem.

It is a sequential structure of algorithms, where the allocation and arrangement optimization of areas of the departments is executed involving best layout project practices by a dynamic process what can reduce man hours dedicated to the design, once the designer has the opportunity to create more alternatives for the facility layout problem to be resolved by a simulation and evaluation process and less computational effort. The Sequential Structure of Algorithms (SSA) proposed in this work is a solution to the facility layout problem that allows a highly iterative process with the project team.

The designer can interact with the stochastic–growth–based loop generating different simulation scenarios by editing new "goals and constraints" systematically analyzing the different facilities layout created on the computer screen, being able to re-edit and arrange as many times as necessary and, in a very reasonable execution time, given the complexity of the facility layout problem to be resolved.

From the research gaps identified, we solve a real problem and describe the steps to build a multi-scenario solution of the shipyard layout problem formulated, solving with meta-heuristics based optimization algorithms and a transition procedure idealized and developed by the authors of this work.

In such procedure, the centroids x and y defined on the grid of the 1st stage, after the topological optimization, are repositioned on the Grid of the 2nd stage with the allocation of each centroid through an algebraic calculation based on the premises of project, primarily those related to departments' closeness conditions defined as constraints, which must be respected during the optimization process for shipyard facility layout in accordance with the required closeness conditions.

Each of the departments has its initial centroid positioned on the geometric grid to the geometrical optimization, right after the end of the first stage and the execution of the transition algorithm; it is the result of the conversion, that is, the transfer between the grids of the two stages considered here. Therefore being, applicable to multiple terrain configurations and problem specificities without needing calibration, solving a real problem with consolidated methods from the literature.

In this context and from what is being proposed, the contribution of this study is based on the implementation of an SSA. This is a novel solution approach that makes use of GA with genetic operators: cycle crossover (CX) and Partially-Matched Crossover (PMX), and a recursive code (RC) in the topological optimization through a discrete representation modeling approach, computational transition procedure for transferring centroids of each department from topological grid to geometrical grid and that makes use of SGAELS to solve facility layout problems through a continuous representation modeling approach in the second stage.

Finally, it should be emphasized that the success of the proposed optimization process was possible through key advances when compared to previous works, with novel optimization approaches capable of meeting the design requirements to solve the problem.

Regarding work limitations, it should be highlighted that the development of optimization methods based on probabilistic algorithms for solving shipyard FLPs should consider all the relevant project requirements, including physical floor space constraints, land "size, location and contour", material flows between departments, and budget constraints.

These project requirements need reliable data, such as, for example, distance between departments with the correct flow of materials for the conception of product flow matrix, often difficult to estimate, particularly in the case of a new facility design; in addition to being more than one objective requiring optimization, becoming a Multi-Objective Facility Layout Problem (MOFLP), and therefore increasing computation effort and time.

The overall structure of this study takes the form of five sections: 1.Introduction; 2. Literature review; 3.Problem and Methods; 4.Results; 5.Conclusion.

2. Literature review

For the specific case of shipyards, [4, 8] defines the facility layout problem as being of the Fixed Materials Location Departments (FMLD) type. However, there is a research gap in literature regarding closeness constraints for this type of FLP which needs to be better studied to contribute to construction befitting mathematical programming solutions for this specific type of production environment.

Through well-defined and controlled closeness conditions by shipyard layout design specifications, material handling costs are potentially reduced and a continuous production flow is ensured [2]. Appropriate sizing of the capacity and the speed of the equipment for transferring the materials throughout the facility, which have different weights and sizes, and go through different departments, also has a strong impact on the performance of this type of system [3–6, 12, 16].

[2,3,17–20] highlight that among the indicators of most relevance that beacons the Facility Layout Problem (FLP) performance is the TMHC, which can be translated as the flow's operational efficiency. However, specific methods of mathematical programming for this type of problem require constraints of closeness to ensure the operation of the Material handling System (MHS) [2, 3].

[2, 3, 12, 14, 16, 21, 22, 23] highlight that between the main algorithms commonly applied to solve the FLP the algorithms Simulated Annealing (SA) and GA have been widely addressed in literature. In this study, the literature review lists the works according to the subsections: 2.1. Facility Layout Problem (FLP), 2.2. Heuristics and meta-heuristics applied in the solution of facility layout problem (FLP), and 2.3. Shipyard Facility Layout Problem (SFLP).

2.1. Facility Layout Problem (FLP)

Facility Layout Problem solution as defined in the Introduction section of this work, has as its main objective to plan a layout that, when constructed, supports all necessary conditions execute its assignments efficiently, with the lowest operational cost. Such operation requires, as a principle, according to [2,17,24,25,26], a material flow as continuous as possible, since the constraints inherent to an inappropriate project are eliminated at its conception and the natural constraints held under control, with the lowest possible impact. In agreement with the literature, the TMHC for this type of problem is relevant because it measures the effectiveness of proximity between departments with closeness constraints, directly reflecting on manufacturing process productivity.

In this case, constraints related to aspect ratio and departments' closeness conditions must be considered as components of the objective function as MOFLP, which requires the application robust optimization techniques.

[27–28] proposes the first MOFLP approach with only two concurrent factors: Minimum Material Handling Cost (MMHC) and maximum Total Closeness Rating (TCR). Author assigns different weights to each of the factors depending on the optimization criteria and priority. Since the 1980s, several works of the MOFLP type have been published, in addition to works of different approaches and types [2,21,22,25,29–35].

The authors of this paper used the Science Citation Index Expanded (SCIE) of Web of Science (WoS), to select papers related to the shipyards MOFLP problem, and found one paper which divides the problem from two Grid representations, discrete and continuous, by [2].

In the same database, the authors also found the works by [36], which deal with the unequal area FLP using the BRKGA, and of [12], which has conducted an extended literature review on facility layout planning. [12] emphasizes that facility layout problem (FLP) has been widely addressed in science, since the second half of the 20th (twentieth) century.

Authors divide literature review works into two groups: 1) The group that deals with more general context [12, 37–45]; and 2) The group that deals with context of specific dimensions [20, 46, 47, 48]. We considered the works on FLP published since 2016, disregarding the following: [43] deals with Survey on Multi-Floor Facility Layout Problem; [44] deals with Review of the Layout Design in Reconfigurable Manufacturing Systems; [50] deals with Overview of Dynamic Facility Layout Planning; and [49] deals with Reconfigurable manufacturing system. Table 1 shows literature review mapping.

Table 1. Systematic literature review mapping on FLP.

References	Year	Citation Indexes (WoS)	Total of references	References Met-heuristic		In the years
				GA	SA	
[42]	2017	83	96	7	4	1992–15
[43]	2017	44	107			
[20]	2017	82	205	39	30	1992–17
[44]	2019	9	133			
[45]	2019	6	172	25	14	1994–16
[50]	2020	2	83			
[49]	2021	14	92	17	3	1997– 18
[12]	2021	3	267	54	34	2010–19

2.2. Heuristics and meta-heuristics applied in the solution of facility layout problem (FLP)

The work by [12] is the most recent literature review of the FLP, with a total of 232 articles. Out of those, 176 are common to those listed in the other three literature reviews indicated in Table 1. [12] used the WoS database and the SCIE. Of the 232 works considered, according to authors, it is important to highlight that 80% of the papers deal with FLP problem applied to classic test problems from the literature with randomly generated theoretical data, i.e. hypothetic problem studies, and only one fifth addressed real-world scenarios and case studies.

However, only 88 papers deal with the application of the Genetic Algorithm (GA) and Simulated Annealing (SA) meta-heuristics. Emphasis on the use of GA meta-heuristic to solve the two optimization stages considered in this work is due to two factors: 1) the complexity of the problem, and 2) the robustness of the theory around GA when compared to the volume of theory on SA.

This problem's complexity causes the solution to be hardly obtained through analytical methods, mainly due to the impact on computational execution time caused when algorithms are used to solve large scale problems, which grow exponentially.

[51] highlight that optimized algorithms were kept at the center of a considerable amount of research work aimed for Quadratic Assignment Problem (QAP) in the late 1950s and early 1960s, which thrived until the development of new methods. The first systematized solutions using computing resources to solve FLP problems with mathematical programming emerged between the decades 1950 to 1980 [52].

The first algorithms and software capable of supporting the conception of layout projects were thought to be a way to automate the set of events related to facility planning, to support the decision-maker in simulating the industrial layout options both economically and financially viable previously to executing the project. Among the solutions cited by the authors there are those from [53–72].

[73] considers that the gained experience in the development of the computing procedures associated with these solutions advanced in the direction of constructing block diagrams, which wouldn't fully answer all the expectations of solutions for FLP problems.

The achieved results represented approximated solutions that would be altered and distorted by specialists to make them exact answers for simpler problems or approximate answers for more complex ones. According to the authors, during the decade of 1990, there was the need to expand the advance of researches emphasizing the development and application of more robust computing procedures, besides block diagrams.

[73] highlights that the research was divided between studying two main combinatorial optimization algorithms to solve integer programming problems, Cutting Planes methods and Branch and Bound algorithm. These algorithms are only effective in the initial steps of FLP solving due to the problems characteristics, having no useful application on further steps.

Beyond this fact, the algorithms and software, until the decade of 1990, emphasized only the MHS cost, not guaranteeing a good solution. The MHS cost is indeed considered by most of the researchers to be the main component of the costing system that controls all the operations of a manufacturing system, but practice has shown that it shouldn't be the only performance indicator.

At the end of the 1990 decade, [14] emphasized the use of robust computing techniques, since analytical approaches ensure the optimal conditions of the solutions as a counterpart of computing time, which rises significantly when the problem's complexity gets higher. The authors recommend heuristic approaches for approximate solutions to FLP from the use of the meta-heuristics SA and GA. Furthermore, based on literature, the authors point out that both meta-heuristics SA and GA started being used to solve a wide variety of combinatorial optimization problems (COPs) during the 90s.

According to [74], the authors [75] realized by analogy that there is a likeness between the results of the research of [76] with the mathematical programming processes used to solve the COPs. In the literature, there is a significant amount of work dealing with the application of SA for the solution of FLPs due to the advantage of the meta-heuristic on avoiding local minimums [14].

As an alternative, according to [77], although it had already been proposed in the decade of 1960, evolutionary computation started contributing to the research field of experimental mathematical computing. Perceived as innovative, it immediately started being applied to the academic environment in different areas of knowledge, even without actual proof of its capacity of converging to a global optimum point. For example, the work of [21] studies the FLP while emphasizing in performance measurement of manufacturing systems, cycle time and productivity from a multi-objective function through GA and simulation.

[77] considers that the 1960 decade was very promising to the Evolutionary Programming (EP), with various contributions from researchers as [78–79], among many others, highlight that the development of the GA is due to the pioneer [80–81]. [77,82,83] claim that the GA prospered for three consecutive decades on the most varied areas of application, including engineering projects, and started to have a peak in interest in the last 15 years [20,84,85]. In the beginning, the GA made the academic community skeptical. Besides the lack of validation in the effectiveness of algorithms, the skepticism was driven by the progress of classical mathematical programming until the 1990 decade, including the theory and procedures created for deterministic heuristics.

Such tasks were part of the dominion of the deterministic procedure of mathematical programming, which had a promising phase since the 1960 decade, especially in the engineering area [77].

It is from the 1990 decade onward that evolutionary computing started being considered an alternative to conventional techniques of mathematical programming used to solve engineering problems, due to the crescent number of methods such as GA, for example. [15,52,82,83] ponder that to keep improving FLP, GA are used as alternatives to creating new optimization mechanisms.

[86] the encoding and decoding of chromosome structures are vital for applying GA to solve Flexible Job Shop Scheduling Problems (FJSP) due to allowing the use of two combined vectors for its chromosomes: the Machine Selection (MS) and the Operation Sequencing (OS).

This work's FLP works in a similar way by also using two combined vectors on the second stage: department selection and department growth.

[2] reinforce that between the most used meta-heuristic approaches by the academy to the solution of FLP, two of them are highlighted: SA and GA, mostly because the FLP represents some applications considered in the literature as NP-hard [14].

In the context described by this paper, [5] highlight different proposals on solving FLP, which are based on sorting the solutions by mono or multi-objective and analysis techniques In the first group, out of 27 publications about mono objective functions, 10 are related to using GA. And between 12 algorithms focusing on multi-objective functions, 3 are related to using GA.

Finally, it should be noted that there is only one work relating to the FLP using the optimization process which comprises topological and geometrical optimizations referenced in the literature, the work to [2].

During geometrical optimization a stochastic growth algorithm is used in the growth–based process with the gradual growth of the geometry for each of the departments being randomly selected, according to the selection criteria as defined within section 3.2.2.

The process occurs until the assigned geometry to the departments satisfies given requirements in area, shape, departments' closeness conditions previously defined with the support of the project team.

Regarding the Sequential Structure of Algorithms, it must be highlighted that scientific contribution is based on the proposal of a robust stochastic optimization process, both with respect to topological optimization and with respect to geometric optimization, including the transition procedure between grids as an innovation, unprecedented in the literature.

2.3. Shipyard Facility Layout Problem (SFLP)

The shipbuilding industry is a typical Engineering-to-Order (ETO) manufacturing environment with a high complexity material flow which uses heavy steel materials and massive intermediate products. Massive intermediate products in this case, are the sub-products produced throughout the manufacturing process. Theses sub-products, in accordance to the project´s specifications, are concatenated throughout multiple stages of manufacturing and /or assembly to create a final product.

Because of that complexity, [87] propose a Product Oriented Design and Construction (PODAC) Cost Model to allow for the ship designers and shipbuilders to understand both cost impact of design alternatives and understand and evaluate the cost of production processes and facility changes based on cost impacts of design, technology and production decisions.

According to [5], a shipyard’s main areas include steel shops, steel stockyards, warehouses, outfitting shops, sub-assembly, panel fabrication, pipe shop, paint shop, general-purpose shop, block erection, dock, and quay. Each of these areas can be assigned to a department at site level.

The objective of shipyard facility layout planning is to minimize the production cycle time while the ship is being built. When facility layout planning ensures that all the design´s premises have been met, especially the closeness conditions requirements, the material handling costs are minimized.

The considerations set out in the previous paragraph are in accordance with the analysis of [2], which considers that the closeness conditions should be very clearly defined within the shipyard layout due to their impact in MHC, which can, in turn, guarantee a continuous production flow with a significantly reduced manufacturing cost.

[5] states that few studies have explored optimization approaches for obtaining shipyard facility layouts designed for more efficient perform industrial operations. [7] developed, applied and verified a methodology for Shipyard Production Areas Optimal Layout Design based on the specifically defined procedure in four phases, by means of previously established closeness relationships. [8,9] have proposed simulation-based shipyard layout design methodologies.

[10] have proposed an integrated shipyard layout design methodology, in which the process for assigning specific locations in the facilities´ physical space based on use of optimization methods and software VIP-PLANOPT. [2] optimized a shipyard layout by minimizing the MHCs. [88] proposes a heuristic algorithm based on greedy algorithms to analyze shipyard spatial arrangement planning problems taking into consideration both time constraints and spatial constraints. Closeness constraints are not considered.

[3] proposed two Evolutionary Algorithms used for topology optimization of shipyard layout design. [5] proposed a two-stage approach for shipyard facility layout selection using Fuzzy Similarity Index (FSI) to assess alternative shipyard layouts obtained from the experience of shipbuilding practitioners with respect to the ideal layout, and the Fuzzy Goal Programming Model (FGPM) to select the alternative layout. Finally, [16] studies the performance of genetic algorithms in order to solve the topology optimization problem of facilities. However there are few studies in the literature evaluating these meta-heuristics while addressing a shipyard facility layout problem. Table 2 shows the works on Shipyard Facility Layout.

Table 2. Literature review on Shipyard Facility Layout.

Item	References	Year	Citation Indexes (WoS)	Citation Indexes (Scopus)	Total of references	Cited to on paper
1.	[7]	2009	3	6	16	3. – 11.
2.	[8]	2009	------	10	12	3. – 7. – 8.
3.	[9]	2010	------	5	11	4. – 8.
4.	[10]	2013	8	12	8	8.
5.	[2]	2017	7	10	15	7. – 8. – 9.
6.	[88]	2018	3	3	27	----------
7.	[3]	2019	------	1	16	9.
8.	[5]	2020	3	4	86	9.
9.	[16]	2021	------	------	76	----------

However, two works using GA for the Shipyard Facility Layout Problem (FLP) may be highlighted: 1) [3], which deal with topologic planning of the FLP problem of a shipyard, and 2) [2], which deals with topologic and geometric planning of the FLP problem of a shipyard. [12] ponder that future work, with an emphasis on real-world FLP applications, should be recommended to reduce the existing research gap on facility layout problems relating to real cases. In the case of naval construction, according to the authors, the only one work that addresses the FLP which the optimization process comprises two stages: topological and geometrical optimizations, with an emphasis on real-world FLP application, it is the work of [2]. In this work the closeness requirements shall ensure with the departments´ adjacency and/or alignment conditions as constraints.

3. Problem and Methods

3.1. Problem Statement

The variables, parameters and constraints considered by the work of [2] were maintained, such as the medium-sized shipyard data (annual production capacity of the order of 150 tonnes) presented in Tables 3, 4 and 5. Table 3 refers to departments and their data, Table 4 refers to shipyard material flow matrix and Table 5 to shipyard departments' constraints.

Table 3. Departments' Data [2]

Department	Description	Required Area	Aspect Ratio (biggest axis/smaller axis)	Topology Optimization	Geometry Optimization
1	Office	9.00	2.00	to be defined	to be defined
2	General Warehouse	28.00	2.00	to be defined	to be defined
3	Stock	15.00	2.00	to be defined	to be defined
4	Pre-treatment	14.00	3.00	to be defined	to be defined
5	Fabrication	50.00	2.00	to be defined	to be defined
6	Panel Line	12.00	2.00	to be defined	to be defined
7	Bulkhead (BHD) fabrication	22.00	4.00	to be defined	to be defined
8	Component Assembly	25.00	2.00	to be defined	to be defined
9	Subassembly	50.00	2.00	to be defined	to be defined
10	Block Assembly	35.00	2.00	to be defined	to be defined
11	1st pre-building	30.00	2.00	to be defined	to be defined
12	Space destined to stocking blocks	40.00	2.00	to be defined	to be defined
13	Pre-outfitting	8.00	2.00	to be defined	to be defined
14	Painting	20.00	4.00	to be defined	to be defined
15	2nd pre-building	144.00	4.00	defined	to be defined
16	Space destined for stocking the 1st pier	50.00	2.00	defined	defined
17	Space destined for stocking the 2nd pier	34.00	2.00	defined	defined

**** to be defined and defined indicate: location to be defined and previously defined location**

Table 4. Material Flow Matrix [2]

From	To	Quantity	From	To	Quantity
3	4	1860t	8	10	120t
4	5	1200t	9	10	1300t
4	7	660t	10	11	700b
5	8	800t	10	13	300b
5	9	95t	11	12	600b
5	10	48t	12	14	600b
7	9	660t	13	11	300b
8	7	4t	14	15	600b
8	9	670t	....	....	....

**** t and b indicate tonnes of steel that is to be transferred and the quantity of blocks that is to be manufactured**

In this case, Departments 15, 16, and 17 were kept fixed, and the remaining Departments were randomly placed. The required area size and aspect ratio of each of the departments as defined in (Table 3) must meet the departments´ shape requirements as specified in the project, subject to the volume constraints of the transported materials between pairs, according to the flow matrix given (Table 4), with respect to design decisions (pre–defined location in the case of the floating dock and quays, indicated in Figure 1). According to [2] the bottom left corner of the shipyard terrain is an unavailable area and the top right corner is adjacent to coastline.

Figure 1 shows real terrain of the shipyard. In Figure 1 the 'not available area' corresponds to departments 18, 19 and 20. Figure 2 indicates the pattern for defining Topological and Geometrical constraints of closeness (alignment–and/or–adjacency–conditions–based) that the FLP must attend.

Table 5. Required departments' closeness conditions as constraints [2]

Department		Required adjacency condition	Required alignment condition
3	4	Yes	Yes
4	5	Yes	No
4	7	Yes	Yes
5	9	Yes	Yes
7	9	Yes	No
9	10	Yes	Yes
11	12	Yes	Yes

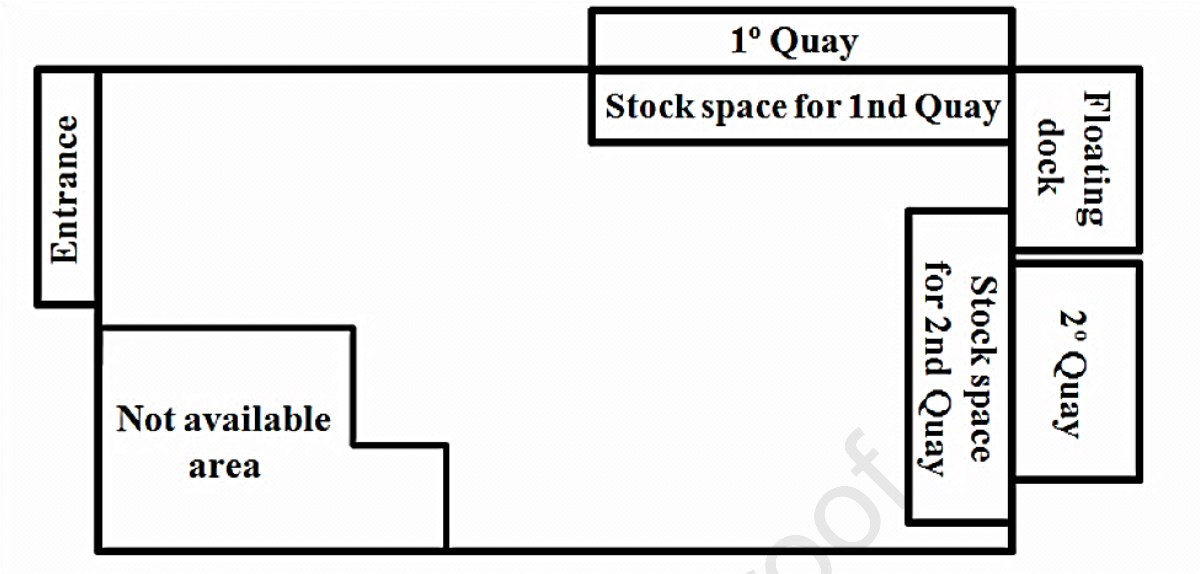

Figure 1. Real Shipyard Terrain. Adapted from [2]

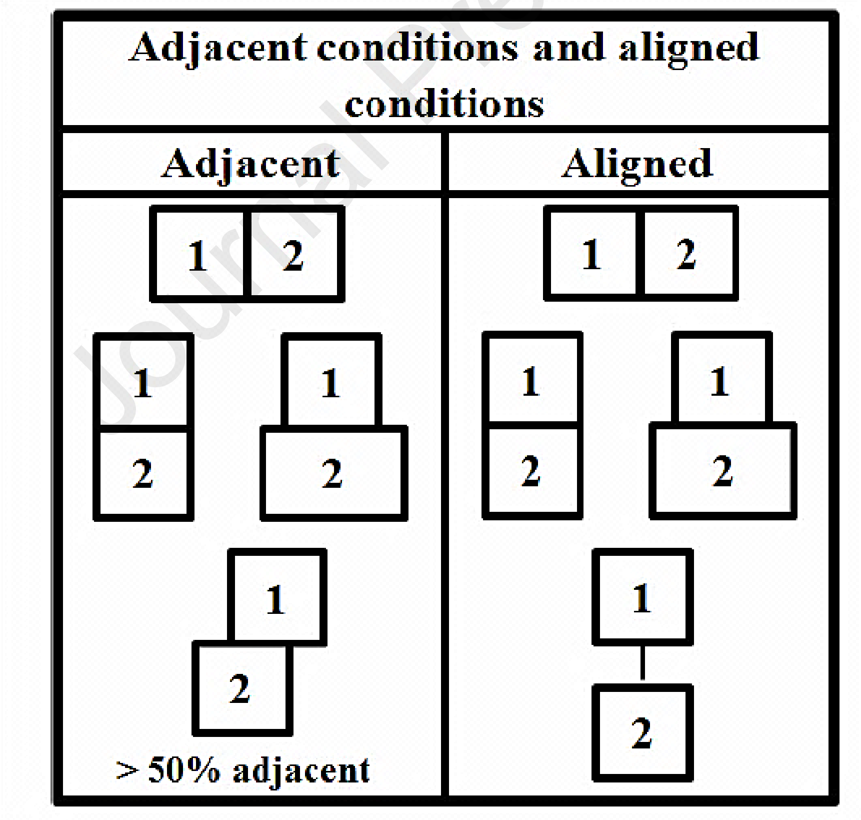

Figure 2. Possible departments' closeness conditions (adjacent conditions and aligned conditions) for topological and geometrical facility layout. Adapted from [2]

3.2. Methods

This paper addresses a sequential structure of algorithms for solving the FLP, an extension of the proposal of [2]. In the 1st stage (topological Optimization); the use of GA includes the transition procedure of the departments' centroid coordinates to transfer from one grid, the topological grid, to another grid, the geometrical grid. During the topological optimization process the departments with adjacent and/or alignment conditions are positioned close to each other.

Transition procedure respects the topological configuration obtained in the 1st stage and the departments´ area and aspect ratio constraints in the process of transferring the centroid coordinates between the grids. The implementation of the transition procedure was done in Python language.

In the 1st stage all tests were performed on a virtual machine, with 8 Virtual CPUs (vCPUs), 12GB Ram and 120GB HD. The implementation was done in software MATLAB Copyright©2018.

On the 2nd stage, aiming to compare the effectiveness of methods, two algorithms were coded:

- SGA;
- SGAELS.

The 2nd stage refers to the geometry optimization process of the departments, with respect to their closeness conditions.

In the 2nd stage all tests were performed on a virtual machine, 8 Virtual CPUs (vCPUs), 12GB Ram and 120GB HD. The implementation was done in Python language.

3.2.1. Topology Optimization (1st stage)

Topology optimization is a mathematical method that allows the determination of the local relationship between departments to the definition of ideal location within a given design space, once that optimizes the TMHC. However, we must specify previously some design decisions, as the adjacency or non-adjacency of one department to another or of a department to the local perimeter constraints.

The GA used for topology optimization is applied to a chromosome structure with 20 genes, which represents the departments´ topology according to grid presented on Figure 3. The topological Grid has squared cells, with an area equal to 1, and with Euclidean distance measurement between departments for topological Optimization.

[2,3] describe the Optimization mathematical problem of the 1st stage according to the definitions in Table 6. With respect to parameters and variables, there is no modification from the 1st stage to the 2nd stage.

Table 6. Mathematical Definitions (1st stage) [2,3]

Sets
D: Set of departments. Departments, indexed by 'd_k' (Table 3)
G: Set of genes (chromosome). In the 1st stage, genes are indexed by letter 'g'
F: Set of fixed position genes (chromosome), In the 1st stage, indexed by letter 'f' (Figure 3) (gray cell)
Mathematical Notation (Parameters)
** the upper letters **tp** and **tv** respectively represent "**topological parameter**" and "**topological variable**".
$f_{i,j}^{tp}$: Material flow from departments i to j – Flow Matrix Data (Table 4)
$c_{i,j}^{tp}$: Transportation cost **(equals to 1 unit)**, Distance Travelled (DT) and volume unit between the departments i and j
$cl_{i,j}^{tp}$: 1 if there is closeness constraint between the departments i and j, 0 if there isn´t constraint
** departments´ closeness conditions are considered as a closeness constraint (Table 5)
p_f^{tp}: represents if the department is assigned to fixed position gene f
N: represents the number of departments
Mathematical Notation (Variables)
x_g^{tv}: represents the department assigned to gene g
$d_{i,j}^{tv}$: represents the Euclidean distance between departments´ centroid i and j
$cx_{d_k}^{tv}$: X coordinate of the centroid – department d_k
$cy_{d_k}^{tv}$: Y coordinate of the centroid – department d_k
$cl_{i,j}^{tv}$: 1 when the departments i and j satisfy the closeness constraint, 0 when they doesn´t satisfy the closeness constraint

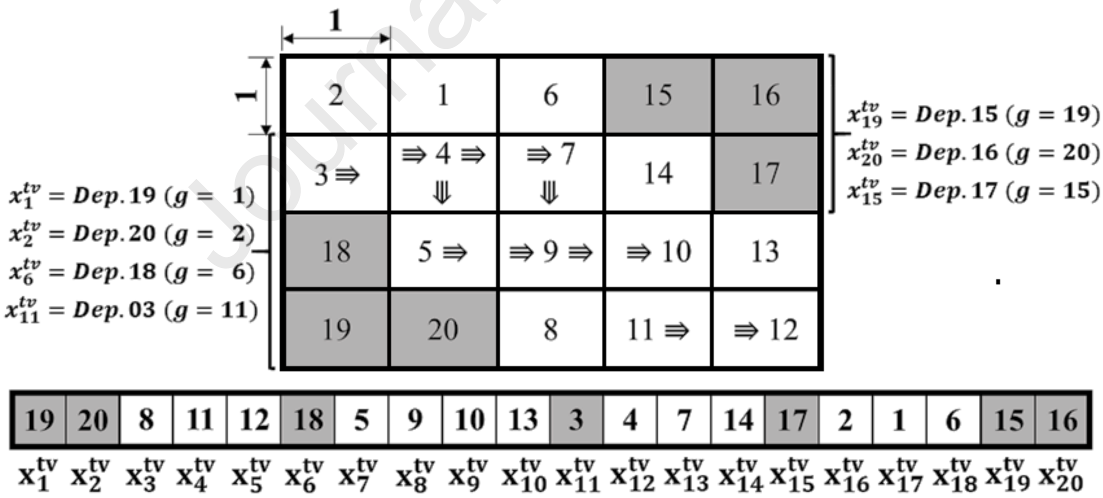

Figure 3. Result of the Topological Optimization (1st stage)

The mathematical expressions (1) to (8) represent the logical model of the 1st stage. The mathematical expression (1) is the objective cost function to minimize the total material handling cost. The mathematical expressions (2) to (7) represent the constraints associated with topology optimization (closeness requirements). The Departments 15, 16, 17, 18, 19 and 20 find themselves fixed according to the mathematical expression (4) that ensures the fixed position genes that must be kept in a predetermined position in chromosome structure.

Fixed position genes represent departments with location and geometry previously incorporated in the initial layout, and the other Departments of Table 3 subjected to the optimization process and, in this case, one of the premises, the material volume being transported between departments. Mathematical expression (5) ensures that all departments are assigned to genes on a chromosome matched with the topological grid cells, at the sequence from the bottom left corner to the top right corner. Mathematical expression (2) represents the closeness constraint by $cl_{i,j}^{tv}$. The mathematical expression (8) defines the 'closeness' constraint according to the departments´ closeness conditions and ensures that the closeness constraints be respected. $d_{i,j}^{tv}$ is the Euclidean distance between the departments on the topological Grid.

$$Minimize\left\{\sum_{i\in D}\sum_{j\in D} f_{i,j}^{tp} \times c_{i,j}^{tp} \times d_{i,j}^{tv}\right\} \tag{1}$$

$$cl_{i,j}^{tv} \geq cl_{i,j}^{tp}; i,j \in D \tag{2}$$

$$cl_{i,j}^{tv} \in \{0,1\}; i,j \in D \tag{3}$$

$$x_f^{tv} = p_f^{tp}; f \in F \tag{4}$$

$$x_i^{tv} \neq x_j^{tv}; i,j \in G \tag{5}$$

$$x_g^{tv} \in \{1,2,\dots,N\}; g \in G \tag{6}$$

$$d_{i,j}^{tv} = \sqrt{\left(cx_i^{tv} - cx_j^{tv}\right)^2 + \left(cy_i^{tv} - cy_j^{tv}\right)^2}; i,j \in D \tag{7}$$

$$cl_{i,j}^{tv} \vee cl_{i,j}^{tv} = 1 \; if \; d_{i,j}^{tv} \leq \sqrt{2}, else \; cl_{i,j}^{tv} = 0 \tag{8}$$

The variable x_g^{tv} indicates the department assigned to each of the genes, and as mentioned previously, fixed position departments are incorporated in the initial layout and are referred to as 'fixed genes'.

In this work, according to the design requirements, we define genes x_1^{tv}, x_2^{tv}, x_6^{tv}, x_{15}^{tv}, x_{19}^{tv}, and x_{20}^{tv} as fixed genes that assume the representation of the departments 19, 20, 18, 17, 15 and 16 assigned (See Figure 3).

Defining the matching between the departments and their respective gene the assignment process starts and the remaining departments are randomly assigned to available genes generating the initial population. Table 5 defines the required departments´ closeness conditions.

For this purpose, GA was coded to replicate the problem detailed in Section 3. The GA framework for MATLAB (See [3]) and the MATLAB software Copyright©2018 were used. Two main factors were taken into account when making this decision:

- Practicality. A robust, complete, and generic GA platform allows you to reduce time and effort during code development, which can be applied to other aspects of the work;
- Customization. By allowing for extensive and deep changes in its operation, the platform does not become an impediment to a free development of the code.

For each test of the defined experiment plan, GA randomly generates a population of N individuals. For each result, the algorithm evaluates fitness function of each individual, selecting the best 50% through a doubles tournament, where only the best survives.

Then, it starts their combination using the crossover and mutation operators, using CX, PMX and binary random mutation. GA´s stopping criterion is the moment at which, after some generations, a delta of 1% is reached between the values of the fitness function in relation to the previous generation.

Figure 4 is the EA flowchart used in the heuristic process of the work. The Algorithm 1 corresponding to the individual generation function used in the AE, it creates the vector solution of size N from the data: number of departments N, list of departments with fixed position and their respective positions fixedPos, list of departments with position constraints dep_constraints. The crossover operators used to create the new generations, as shown in Figure 4, are described in Algorithms 2 and 3.

Once elements of the crossover segment have been explored the remaining part of the descendants can be fulfilled from the P2. Second child is raised in similar way. The mutation is based on the Swapping technique: this type of mutation selects two genes randomly and swaps their positions (See [89]). This operator preserves most adjacency information [90].

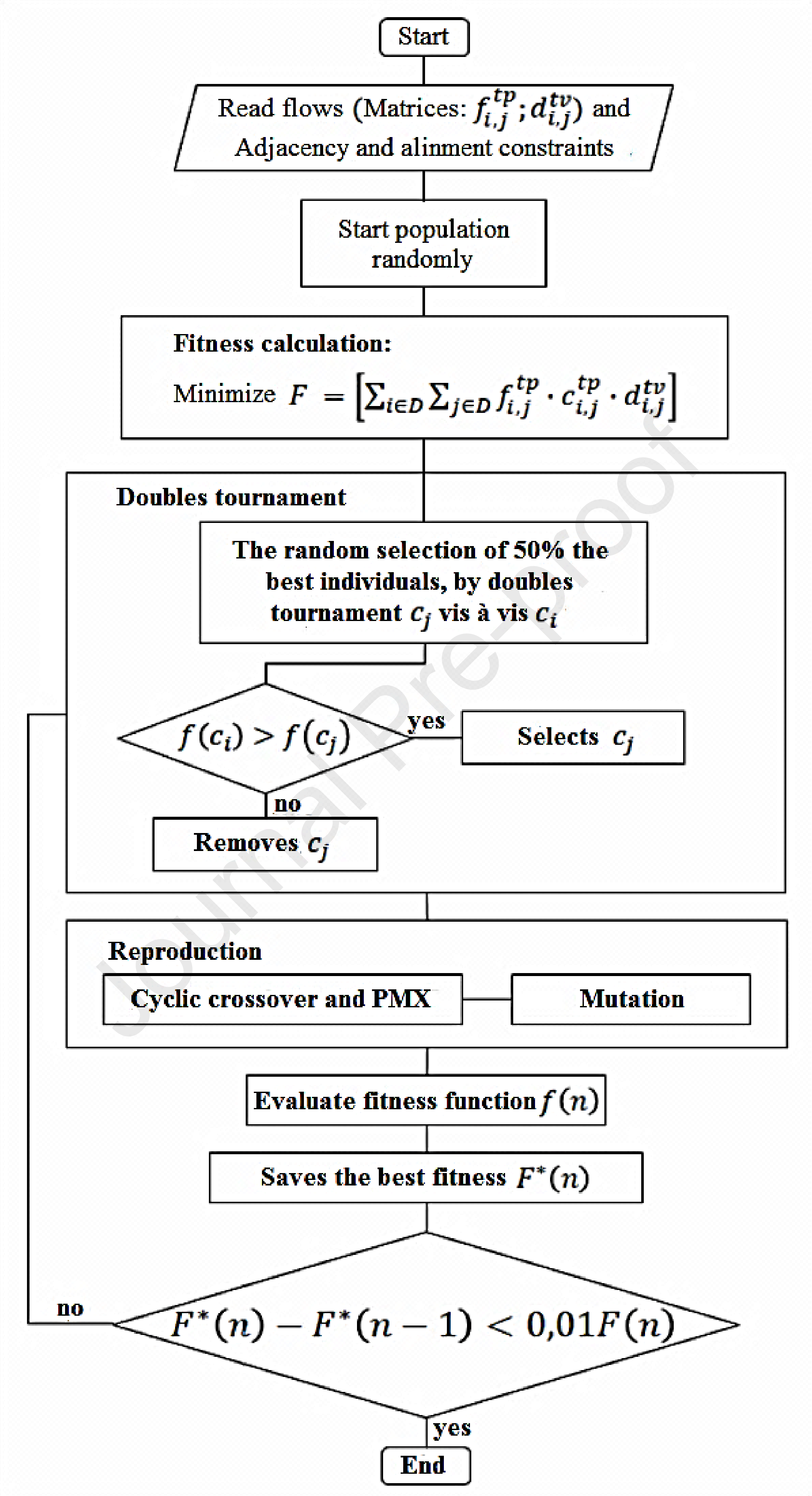

Figure 4. Flowchart of the proposed GA with recursive code, CX, PMX and binary random mutation. See [3].

Algorithm 1 Individual Creation Function. See [3]

1: Create vector **solution** of size N;
2: If there are departments with a fixed position;
3: Insert them in the **solution** vector in the required positions;
4: If there are departments with position restrictions;
5: Store the current state of **solution**;
6: For each item in **dep_constraints**
7: Check if any of these departments are already inserted;
8: If yes
9: Insert the department that does not yet have a position. Its position must be randomly chosen from a sample space composed only of positions that do not violate the mandatory restrictions;
10: If it is not possible to restore the state of **solution** stored in step 6 and go back to step 7;
11: If not
12: Insert the first department completely randomly;
13: Insert the department that does not yet have a position. Its position must be randomly chosen from a sample space composed only of positions that do not violate the mandatory restrictions;
14: If it is not possible to restore the state of **solution** stored in step 6 and go back to step 7;
15: Insert the other departments in a totally random way in the empty positions;

Algorithm 2 Cyclic crossover [90]

1: Each allele comes from one parent jointly with its position:
2: Carry out cycle of P1 alleles.
3: Start with the first unused position and allele of P1.
4: Look at the allele in the same position in P2.
5: Go to the position with the same allele in P1.
6: Add this allele to the cycle.
7: Repeat step 4 through 6 until you arrive at the first allele of P1.
8: Put the alleles of the cycle in the first child on the positions they have in the first parent.
9: Take next cycle from second parent.

Algorithm 3 PMX. Procedure for parents P1 and P2 [90].

1: Choose random segment and copy it from P1.
2: Starting from the first crossover point look for elements in that segment of P2 that were not been copied.
3: For each of these (say i), look in the offspring to see what element (say j) has been copied in its place from of P1.
4: Place i into the position occupied by j in P2, since we know that we will not be putting j there (as we already have it in our string).
5: If the place occupied by j in P2 has already been filled in the child k, put i in the position occupied by k in P2.
6: Having dealt with the elements from the crossover segment, the remaining positions in this offspring can be filled from P2, and the second child is created analogously with the parental roles reserved.

Regarding use of PMX; and use a recursive code in the topological optimization stage, defined as the 1st stage, should be highlighted: for each test of the defined experiment plan, the GA randomly generates population of N individuals for each of the results, the algorithm evaluates the fitness of each individual, selecting the best 50% through a doubles tournament, where only the best survives. Then, it starts to combine them through the crossover and mutation operators, using cyclic crossover, PMX crossover and binary random mutation. GA´s stopping criterion is the moment at which, after some generations, a delta of 1% is reached between the values of the fitness function in relation to the previous generation. Genetic Algorithm operates through mechanisms of natural selection with an emphasis on the survival of the fittest individual.

- Cyclic crossover [90].

1) Each allele comes from one parent jointly with its position:

a) Carry out cycle of P1 alleles.

b) Start with the first unused position and allele of P1.

c) Look at the allele in the same position in P2.

d) Go to the position with the same allele in P1.

e) Add this allele to the cycle.

f) Repeat step 4 through 6 until you arrive at the first allele of P1.

2) Put the alleles of the cycle in the first child on the positions they have in the first parent.

3) Take next cycle from second parent.

- Partially-mapped crossover operator (PMX). Procedure for parents P1 and P2 [90].

1) Choose random segment and copy it from P1.
2) Starting from the first crossover point look for elements in that segment of P2 that were not been copied.
3) For each of these (say i), look in the offspring to see what element (say j) has been copied in its place from of P1.
4) Place i into the position occupied by j in P2, since we know that we will not be putting j there (as we already have it in our string).
5) If the place occupied by j in P2 has already been filled in the child k, put i in the position occupied by k in P2.
6) Having dealt with the elements from the crossover segment, the remaining positions in this offspring can be filled from P2, and the second child is created analogously with the parental roles reserved.

Figures 5 and 6 represent the operator's steps. Having worked with the elements of the crossover segment, the remaining part of the offspring can be filled with P2. The second child is created analogously, according to Figure 7.

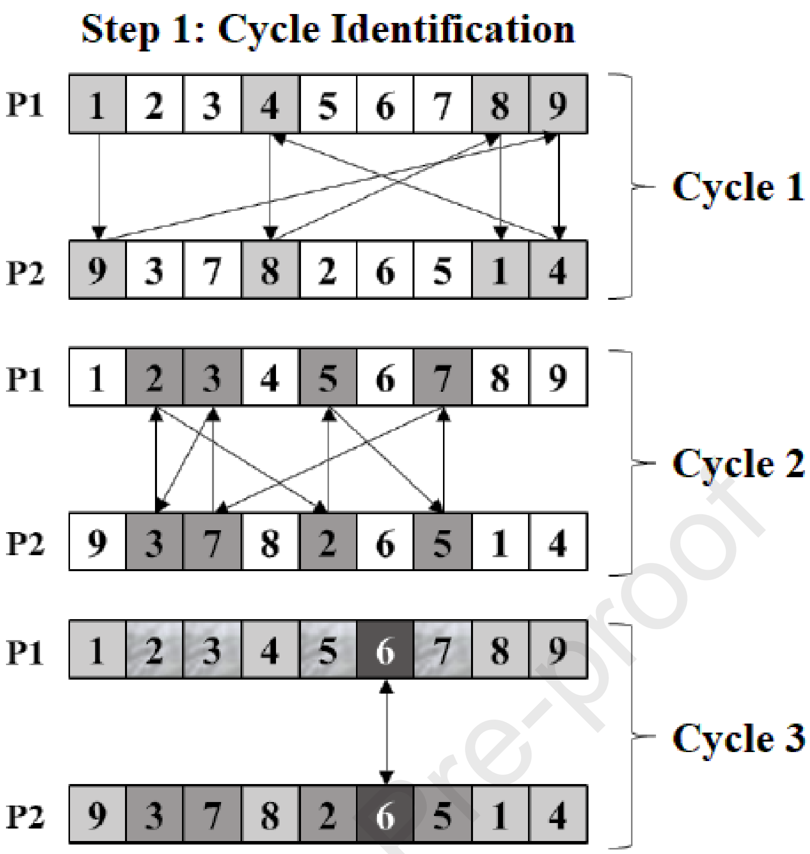

Figure 5. Cyclic crossover, step 1 [90].

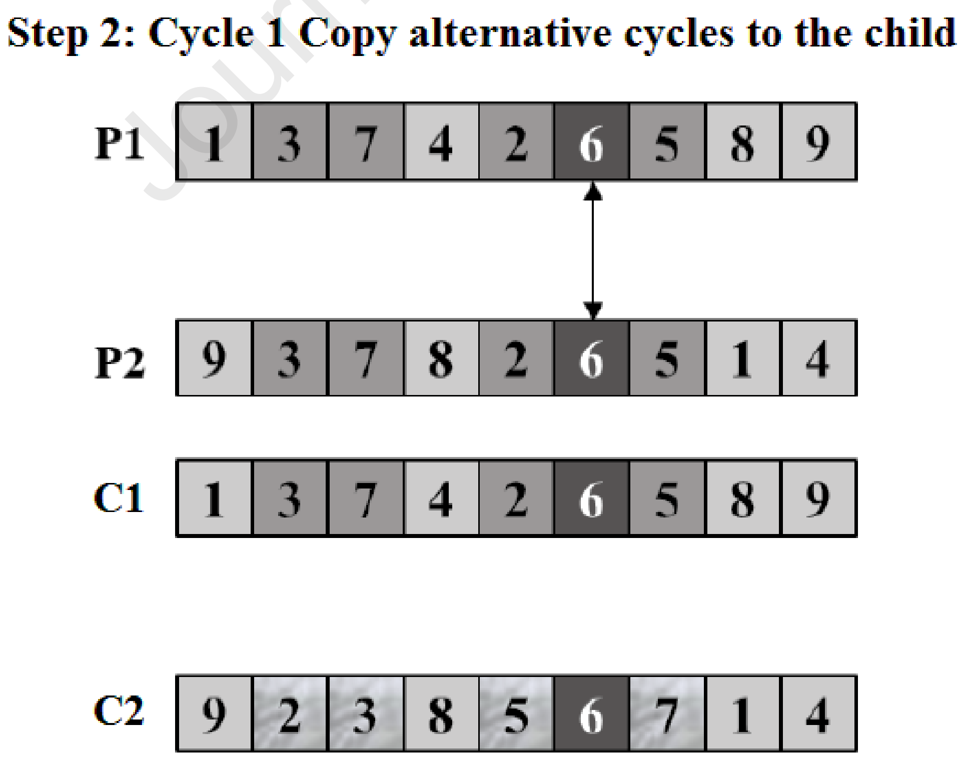

Figure 6. Cyclic crossover, step 2 [90].

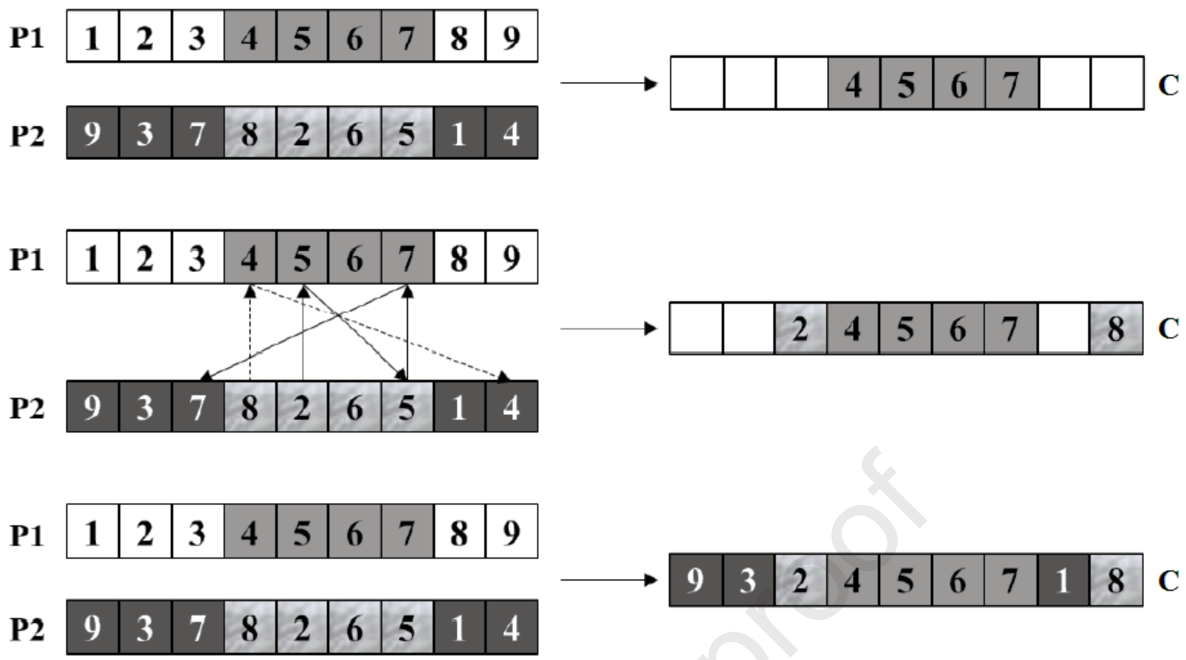

Figure 7. Crossover PMX [90].

- Mutation:

Swapping: This type of mutation selects two genes randomly and swaps their positions. This operator preserves the required departments´ closeness constraints (adjacency–and/or–alignment–conditions–based) information [90], according to Figure 8.

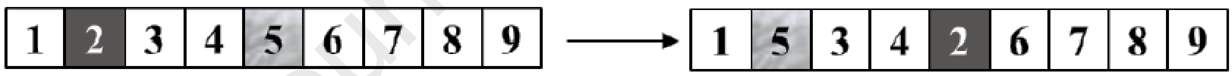

Figure 8. Swapping mutation [90].

As a consequence, it does not guarantee obtaining the best possible solution, but it allows obtaining good solutions for NP-hard problems, considered complex and NP-complete [91, 92]. The crossover operators used to create new generations, as shown in Figure 4, is described.

In this work, the PMX technique was chosen because it respects the restrictions of the problem, which presents ordered chromosomes without repetition, that is, each gene has a limited scope of possible values and there cannot be two or more genes with the same value in one single chromosome.

It is also worth highlighting, according to the argument of [93, 94] that the crossover function is an important procedure of a GA. During the reproduction step in a GA two chromosomes are combined to generate a new individual. At this moment, several crossover techniques can be applied, each one having specific characteristics that make them more or less effective, which motivated the authors of this work to develop the genetic algorithm applied in the first stage as proposed with proven results. Emphasizing one of the scientific contributions of this work.

Therefore, in the case of the problem addressed in this study, we note that a totally random algorithm would not work with the required efficiency, making it necessary to create a function that walks through the chromosome to be created and randomly chooses a value for each position, taking into account a specific scope of the gene in question, having only values that when used in that position they would not disrespect any restrictions. In situations like this, a recursive algorithm proves to be much more efficient than an iterative one, as it facilitates backtracking (a technique that consists of going back to return to the previous step if the next step cannot be executed).

3.2.2. Geometry Optimization (2nd stage)

The geometrical Grid represents the shipyard's real terrain and for the considered shipyard have its dimensions expanded from the 5x4 cells Grid (topological Optimization) to a 46x22 cells Grid (geometrical Optimization), according to the panels dimension (length x width) and major blocks size (length x width x height) to be transported on shipyard manufacturing system. In this work we considered the techniques specifications related to the shipyard´s production capacity described in the work of [2].

In order to be used in the present work, a transition procedure was codified to adapt the centroid's coordinate each department defined by topology Optimization to the geometrical Grid, whilst complying with problem constraints.

The mathematical expressions 9 to 19, described in the sequence, represent the logic of the 2nd stage model (Objective Function and Constraints), according with the definitions of Table 7.

$$\sum_{i \in D} \sum_{j \in D} f_{i,j}^{gp} \cdot c_{i,j}^{gp} \cdot d_{i,j}^{gv} \tag{9}$$

$$\sum_{d \in D} \frac{\left| ar_{d_k}^{gp} - ar_{d_k}^{gv} \right|}{ar_{d_k}^{gp}} \tag{10}$$

$$\sum_{d \in D} \left| as_{d_k}^{gp} - as_{d_k}^{gv} \right| \tag{11}$$

$$Min.[(\omega_1 \times Eq.9) + (\omega_2 \times Eq.10) + (\omega_3 \times Eq.11) + p^{gv}] \tag{12}$$

$$d_{i,j}^{gv} = \left|cx_i^{gv} - cx_j^{gv}\right| + \left|cy_i^{gv} - cy_j^{gv}\right|; i,j \in D \tag{13}$$

$$ar_{d_k}^{gv} = l_{d_k}^{gv} \cdot s_{d_k}^{gv}; d \in D \tag{14}$$

$$as_{d_k}^{gv} = \frac{l_{d_k}^{gv}}{s_{d_k}^{gv}}; d \in D \tag{15}$$

$$\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} ad_{i,j}^{gp}\left(1 - ad_{i,j}^{gv}\right); \ \ i,j \in D \tag{16}$$

$$\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} al_{i,j}^{gp}\left(1 - al_{i,j}^{gv}\right); \ \ i,j \in D \tag{17}$$

$$p^{gv} = (\omega_4 \times Eq.16) + (\omega_5 \times Eq.17) \tag{18}$$

The transition procedure receives the complete shipyard data: departments (quantity, topological order, and position, size, and aspect ratio constraints), flow matrix and TMHC. The conversion result is described in Figure 9.

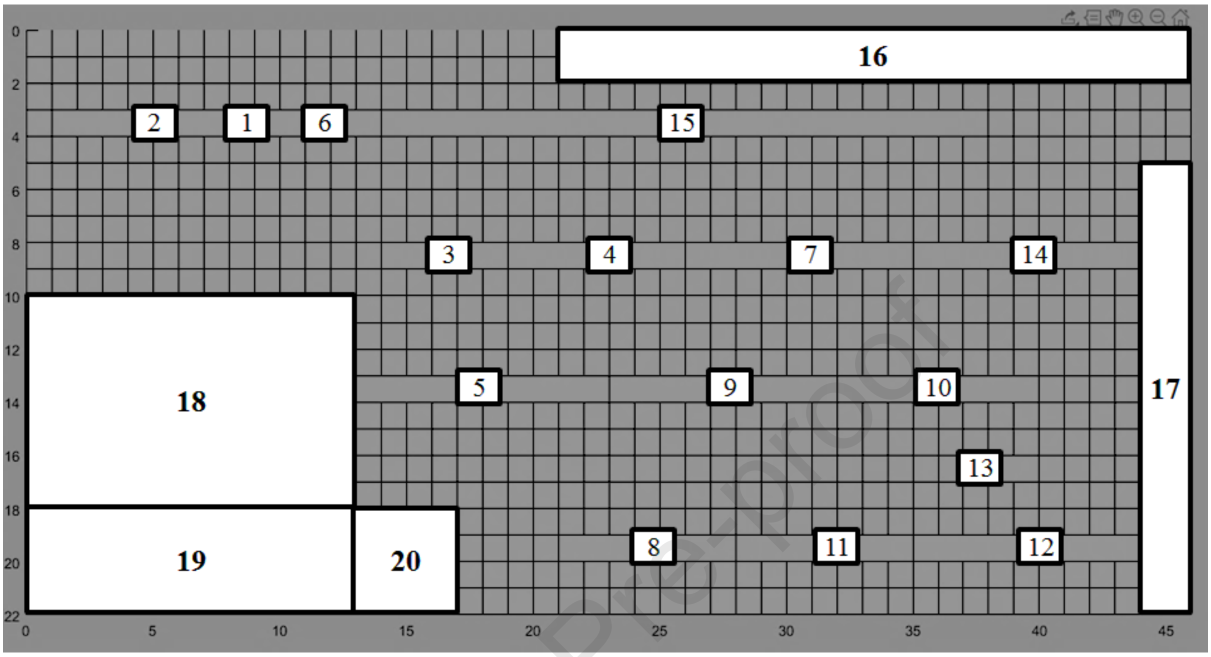

Figure 9. Geometrical Grid Representation - Shipyard Terrain with distributed centroid coordinates

Figure 9 illustrates the distribution of the departments' centroid coordinates in the Geometrical Grid based on the topology optimization result after application Transition Code shown in Supplementary Material (Section A). The departments 19, 20, 18, 17 and 16 have fixed positions on the 2^{nd} stage.

The Mathematical Expression (12) is the objective cost function to minimize the total material handling cost in the second stage. The Mathematical Expressions 9, 10, 11 and 18 are sub functions of the objective function represented by Mathematical Expression (12).

The penalty cost inhibits the occurrence of infeasible unsatisfactory solutions given departments´ closeness conditions, once the Mathematical Expression (12) recalculates the conditions every time centroid departments´ coordinates adjust during the geometry Optimization process the facilities layout.

The mathematical expression (13) calculates Manhattan distance between departments i and j. Mathematical expression (14) calculates the size of the area of departments after iterations. Mathematical expression (15) calculates the aspect ratio. First step each iteration of geometry optimization process calculates the probability each department based on difference between required and achieved area ($\left|ar_j^{gp} - ar_j^{gv}\right|$) and, then, the selection of the department to be modified by that iteration using the roulette method.

Table 7. Mathematical Definitions (2nd Stage) [2]

Sets
D: Set of departments. Departments, indexed by 'd_k' (Table 3)
Mathematical description – Parameters
** upper letters **gp** and **gv** indicate "**geometric parameter**" and "**geometric variable**".
$f_{i,j}^{gp}$: material flow between departments i and j (Flow Matrix Data – from i to j) (See Table 4)
$c_{i,j}^{gp}$: Transportation cost **(equals to 1 unit)** per DT
$ar_{d_k}^{gp}$: department´ required area d_k (See Table 3)
$as_{d_k}^{gp}$: department´ required aspect ratio d_k (See Table 3)
$aj_{i,j}^{gp}$: 1 departments i and j require the adjacency condition, 0 otherwise (See Table 5)
$al_{i,j}^{gp}$: 1 departments i and j require the alignment condition, 0 otherwise (See Table 5)
p_f^{gp}: Predetermined departments to fixed gene f
$\omega_1(10^{-8})$ Weight factor for TMHC
$\omega_2(10)$ Weight factor for area
$\omega_3(10)$ Weight factor for aspect ratio
$\omega_4(200)$ Weight factor for adjacency
$\omega_5(400)$ Weight factor for alignment
N: Number of departments
Mathematical description – Variables
x_g^{gv}: Department assigned to gene g
$ar_{d_k}^{gv}$: Achieved area for department d_k
$as_{d_k}^{gv}$: Achieved aspect ratio for department d_k
$aj_{i,j}^{gv}$: 1 departments i and j adjacent, 0 otherwise
$al_{i,j}^{gv}$: 1 departments i and j aligned, 0 otherwise
$d_{i,j}^{gv}$: Manhattan distance between departments
$l_{d_k}^{gv}$: Longer axis department d_k
$s_{d_k}^{gv}$: Shorter axis department d_k
$cx_{d_k}^{gv}$: coordinate department (d_k)
$cy_{d_k}^{gv}$: coordinate department (d_k)
$sel_{d_k}^{gv}$: Probability of selecting department d_k
p^{gv}: cost penalty

Probability calculation to build the roulette system is achieved by the Mathematical Expression (19). Table 8 shows the mathematical expression of Performance Indicators calculated for each an iteration.

$$Sel_j^{gv} = \frac{\left|ar_j^{gp} - ar_j^{gv}\right|}{\sum_{i \epsilon D}\left|ar_i^{gp} - ar_i^{gv}\right|} \tag{19}$$

The higher the Sel_j^{gv} value, the department j is more likely to be selected. At this condition, the biggest difference between the required area and currently achieved area was assigned to department j.

Table 8. Performance Indicators [2]

$\left(\frac{\left|ar_{d_k}^{gp}-ar_{d_k}^{gv}\right|}{ar_{d_k}^{gp}}\right)$	calculates satisfaction rate of the department´s required area
$\left(\left|as_{d_k}^{gp} - as_{d_k}^{gv}\right|\right)$	calculates satisfaction rate of the department´s required aspect ratio

The department will grow if there is a positive difference (required area > achieved area) or shrink if there is a negative difference (required area < achieved area). After the selection, the algorithm calculates the probability of each direction of modification based on the required and achieved aspect. Figure 10 (adapted from [2]) shows (a) Modes of direction definition and (b) Operator example.

a) Different types of direction definition considered by the 2nd stage with SGAELS. According to Figure 10, two modes define the directions and four directions are assigned to each mode. Each direction has a different probability according to the gap between the required aspect ratio and current aspect ratio. When the current aspect ratio is greater than required aspect ratio during the growth-based process high probability, according to the probabilities described in Table 9 is given to select the shorter axis for growth to satisfy the required aspect ratio; and
b) Represent the example of displacement–based operator (push): the department selected to grow to the right pushes the other departments when they occupy the space needed. Selected department grows and causes these departments to undergo an opposite process of shrink.

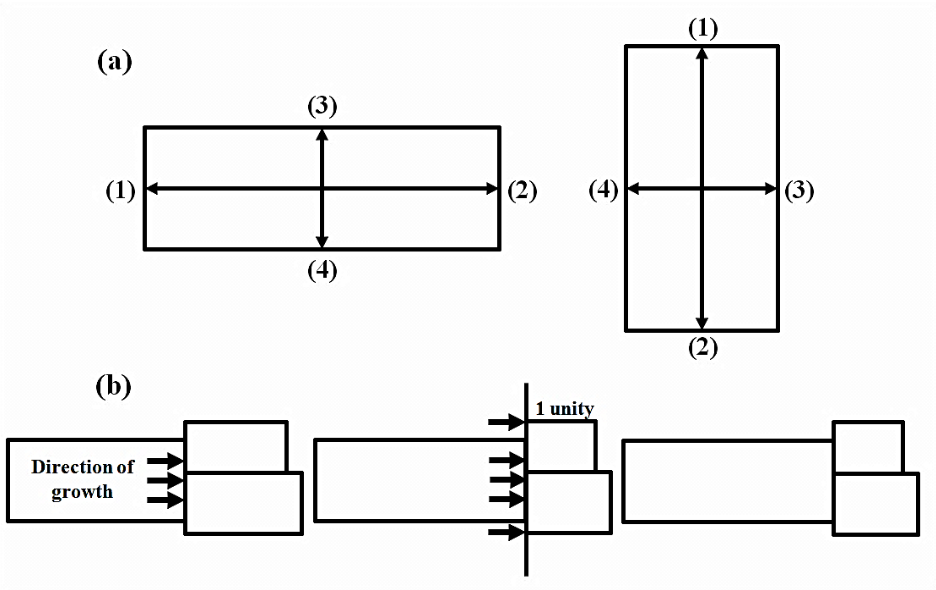

Figure 10. (a) Modes of direction definition and (b) operator example. Adapted from [2]

If any department prevents growth, the displacement (Push) function is executed in order to move them away, allowing modification. Next, the department is modified, and so are the neighboring departments; it is necessary to maintain alignment. In this moment the objective value of the achieved configuration is calculated and compared with the previous one.

Upon an improvement, the new value is immediately adopted, otherwise if the value is worse there is a small probability of being adopted nevertheless or (in high probability) being discarded and rolled back to the previous state. The operators added by [2] are still present on this version of the code:

- Displacement–operator (push): in case there is another department that obstructs the growth of the chosen one, the algorithm tries to move it by unity in the direction of growth.
- Closeness–operator (attract): modifiers were added to the direction probability calculation in order to influence the department to grow in the direction of other with whom there is a closeness requirement.
- Recover previous solution (Recovery): all bad solutions have a small probability of being kept as the best answer. This probability gets progressively smaller throughout the continuation of the problem. If a subsequent iteration worsens the result, the algorithm discards the solution and return to the conditions of the solution result based on previous iterations.

Table 9 shows the percentage of growth–based and shrinkage–based probabilities on both the SGA and SGAELS, according to [2].

Table 9. Percentage probabilities of selecting of each direction (growth–and–shrinkage–based)

as_j^{gp}	$\leq \left(\frac{as_j^{gv}}{2}\right)$	as_j^{gv}	$\geq 2 \times as_j^{gv}$	as_j^{gv}	as_j^{gv}
Percentage probabilities of selecting of each direction (growth–based**)**					
Direction (1) ↑	$(5+\alpha)\%$	$(15+\alpha)\%$	$(45+\alpha)\%$	$(35+\alpha)\%$	$(25+\alpha)\%$
Direction (2) ↑	$(5-\alpha)\%$	$(15-\alpha)\%$	$(45-\alpha)\%$	$(35-\alpha)\%$	$(25-\alpha)\%$
Direction (3) ↑	$(45+\beta)\%$	$(35+\beta)\%$	$(5+\beta)\%$	$(15+\beta)\%$	$(25+\beta)\%$
Direction (4) ↑	$(45-\beta)\%$	$(35-\beta)\%$	$(5-\beta)\%$	$(15-\beta)\%$	$(25-\beta)\%$
Percentage probabilities of selecting of each direction (shrinkage–based**)**					
Direction (1) ↓	$(45+\alpha)\%$	$(35+\alpha)\%$	$(5+\alpha)\%$	$(15+\alpha)\%$	$(25+\alpha)\%$
Direction (2) ↓	$(45-\alpha)\%$	$(35-\alpha)\%$	$(5-\alpha)\%$	$(15-\alpha)\%$	$(25-\alpha)\%$
Direction (3) ↓	$(5+\beta)\%$	$(15+\beta)\%$	$(45+\beta)\%$	$(35+\beta)\%$	$(25+\beta)\%$
Direction (4) ↓	$(5-\beta)\%$	$(15-\beta)\%$	$(45-\beta)\%$	$(35-\beta)\%$	$(25-\beta)\%$

However, the SGALES to include the Electre Method and Local Search Method. Electre method involves a group of decision-making methods that allows an individual, or algorithm, to choose an action from a group of possible actions.

For this purpose, a weighting system is created that defines a hierarchy of importance among the available actions. Inspired by the method, the system applied in the algorithm dynamically defines the weight of each constraint.

If, for example, a currently running solution respects more position constraints than approximation constraints, the algorithm will adapt the weights so that the position constraints receive proportionately more attention [22,84,95], according to Figure 11.

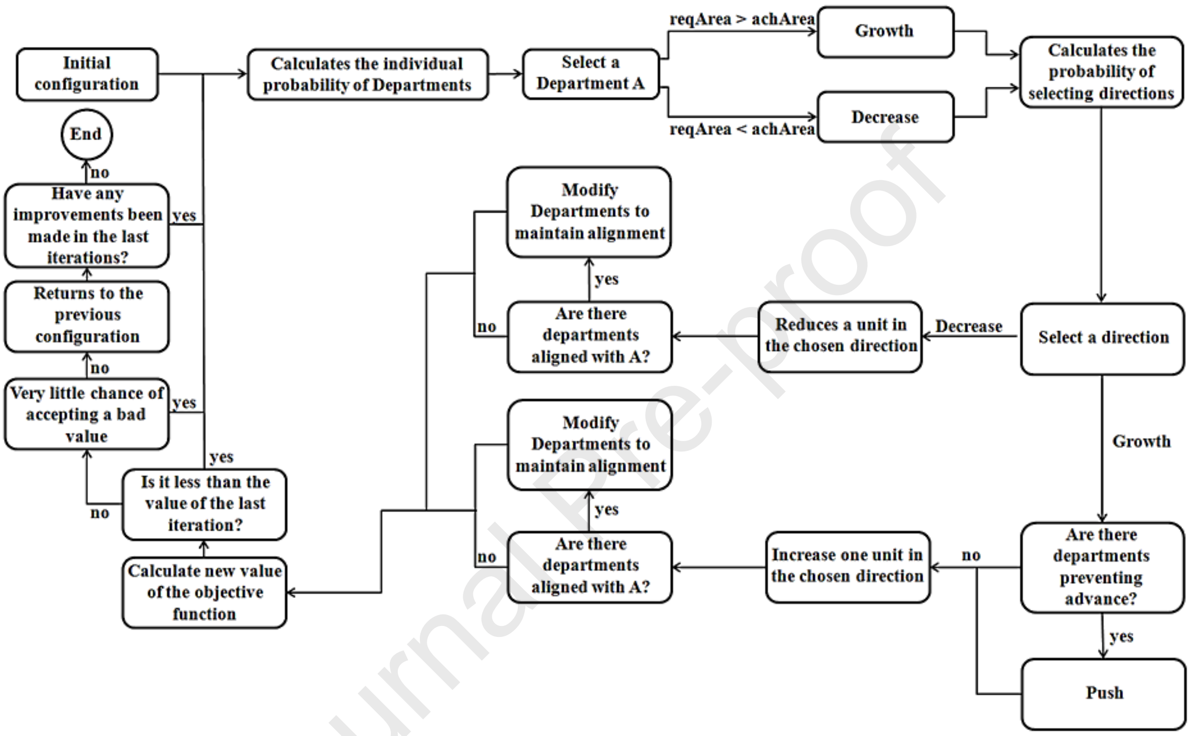

Figure 11. SGAELS flowchart

The SGAELS has a reduced execution time but tends to achieve global optimal results less frequently. Local Search Engine applied increases its efficiency. At the end of the algorithm execution, if there are departments that did not meet some proximity constraint, Local Search Engine is executed.

Positions of the centroid coordinates of each of these departments are explored, modifying their positions (when possible) to bring them closer to the departments with which they have incomplete constraints.

This process is done to respect the area limits provided, as well as the constraints previously reached, making it impossible for the new result to be inferior to the one presented by the SGA and the Electre methods. Our Local Search Engine as described in Figure 12 seeks continuous improvement initial solutions to obtain better solutions at the end of each simulation.

Local Search Procedures, when integrated with other optimization algorithms, usually help to improve the result, it is a good practice applied to improve the performance of optimization process [96].

When subsequent iterations do not improve the result achieved, the algorithm stops. Figure 11 show the flowchart of SGAELS and the Figure 12 show the Local Search method flowchart.

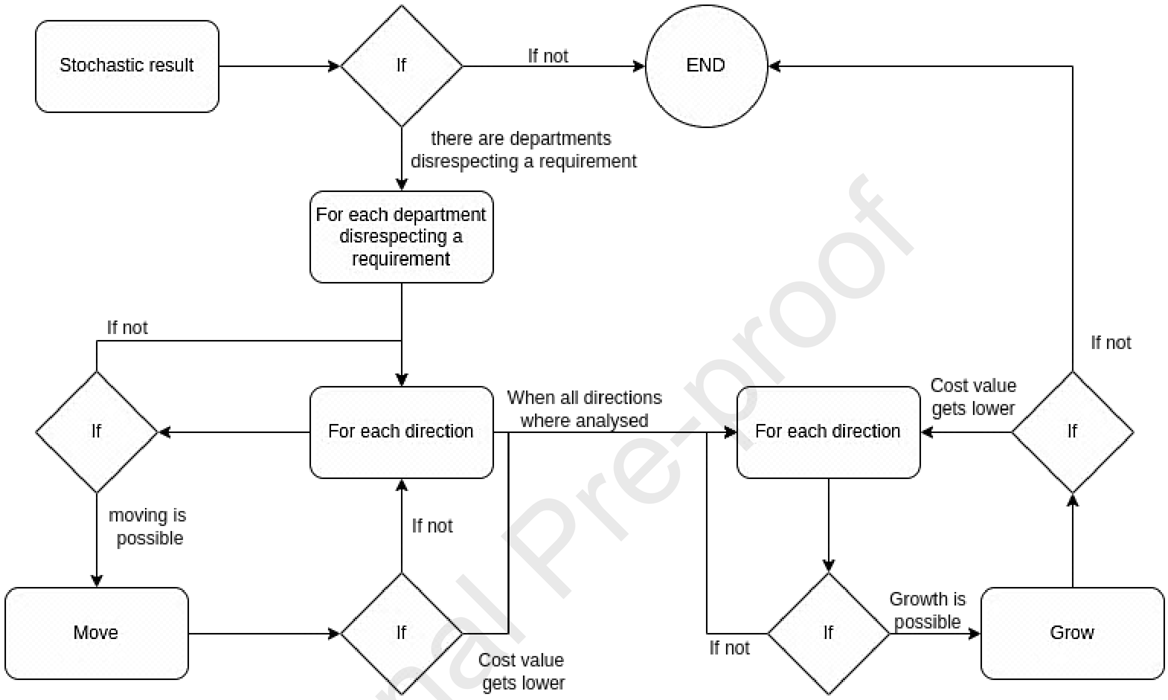

Figure 12. Local Search method flowchart

4. Results

4.1. 1st Stage Results

After 100 iterations, GA determines a topological configuration described in Figure 3. It is an optimal topological configuration with the minimal cost of 11,816 (number of individuals equal to 800), according to the results of Figure 13. Variation of mutation rate is $0.0640 \leq P_m \leq 0.0900$ and the variation of crossover rate is $0.6230 \leq P \leq 0.8330$.

The optimal topological configuration is used for geometry optimization in the second stage. The transfer of department centroids from the topological grid to the geometrical grid was performed by the Algorithm of Transition Procedure.

The required departments´ closeness constraints (adjacency–and/or–alignment–conditions–based) were fulfilled and the departments that have been assigned to the fixed position genes located at their initial position as previously defined.

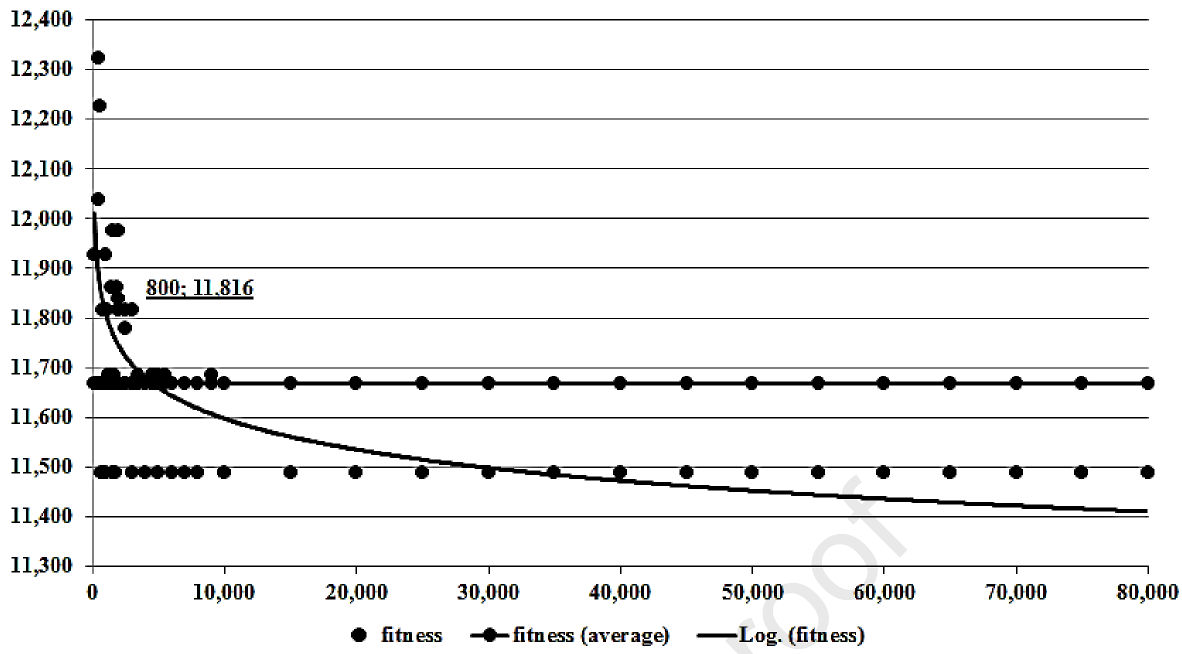

Figure 13. Fitness variability in function of number of individual.

4.2. 2nd Stage Results

From the centroid coordinates distribution in the geometrical grid, three layout options were selected: two (scenarios 1 and 2) after the execution of SGAELS and one after the execution of SGA, similar to the result obtained in [2]. The results obtained with the calculation of the mathematical expressions (14) and (15) from data for each layout option can be found in Table 10.

Figures 14 and 17 shows the layout of each one of the scenarios as well, obtained with the SGAELS, as Figures 15, 16, 18 and 19 shows the dispersion of both the required area and aspect ratio of scenarios when compared to the results of [2]. Table 11 shows the classification of the scenarios based on the total cost obtained.

The 2nd scenario of the SGAELS, due to the grid configuration, was considered the best. Its total cost is lower than that obtained in [2] considering the dimension constraints: area and aspect ratio.

Analysis of Table 11 is perceivable that all the results obtained suffered a slight increase in cost compared to the results obtained by [2]. On the other hand, while analyzing the cost reduction due to the achieved aspects, the total penalty value is significantly smaller. Figures 15, 16, 18, and 19 detail these characteristics.

Table 10. Scenarios Results (mathematical expressions (14) and (15))

Dep.	Area Satisfaction (%) (14)			Aspect Ratio Satisfaction (15)		
	SGA [2]	SGAELS Scenario 1	SGAELS Scenario 2	SGA [2]	SGAELS Scenario 1	SGAELS Scenario 2
1	88.89%	88.89%	88.89%	0.00	0.00	0.00
2	100.00%	100.00%	85.71%	0.25	0.25	1.33
3	93.33%	80.00%	53.33%	1.50	1.00	0.00
4	85.71%	100.00%	100.00%	0.00	0.50	0.50
5	100.00%	100.00%	100.00%	0.00	0.00	0.00
6	100.00%	100.00%	66.67%	0.67	0.67	0.00
7	100.00%	90.91%	81.82%	1.50	1.00	0.50
8	90.91%	88.00%	88.00%	0.67	0.25	0.25
9	88.00%	100.00%	100.00%	0.00	0.00	0.00
10	100.00%	100.00%	100.00%	0.60	0.60	0.60
11	100.00%	100.00%	93.33%	0.00	0.80	0.00
12	100.00%	100.00%	100.00%	0.50	0.40	0.40
13	100.00%	100.00%	100.00%	0.00	0.00	0.00
14	100.00%	80.00%	80.00%	1.00	0.00	0.00
15	100.00%	100.00%	100.00%	0.00	0.00	0.00

Table 11. Cost Results: Area and Aspect Ratio (Scenarios)

Scenarios	Cost: TMHC (ω_1)	Cost: Area and Aspect Ratio		Cost: Total
		Cost: Area (ω_2)	Cost: Aspect Ratio (ω_3)	
SGA [2]	0.0010204	49.6306	18.6869	68.3185
SGAE **Scenario 1**	0.0009774	13.0730	49.1670	62.2410
SGAELS **Scenario 1 (see Figure 14)**	0.0009356	07.2202	54.6667	61.8878
SGAE **Scenario 2**	0.0010115	38.0474	24.9924	63.0408
SGAELS **Scenario 2 (see Figure 17)**	0.0010540	15.3990	37.0000	52.4000

Similarly to Figures 14 and 17, it presents a solution close to [2] while allowing departments 14 and 15 to be positioned differently, reducing the final cost.

As observed in Figures 14 and 17, the layout configurations achieved by SGAELS are similar to those obtained by [2]. However, material flow between departments 14 and 15 in the new configurations becomes optimized due to the shorter distance between both departments.

Figure 16 explicit that the departments on the same scenario obtained different satisfaction rates on the aspect values in relation to the original work, having only 1 of them achieved total satisfaction, 3 getting close to the result showed by [2] and only 3 deviating from the objective (departments 4, 11, and 12). The result of Figure 19 is similar to Figure 16.

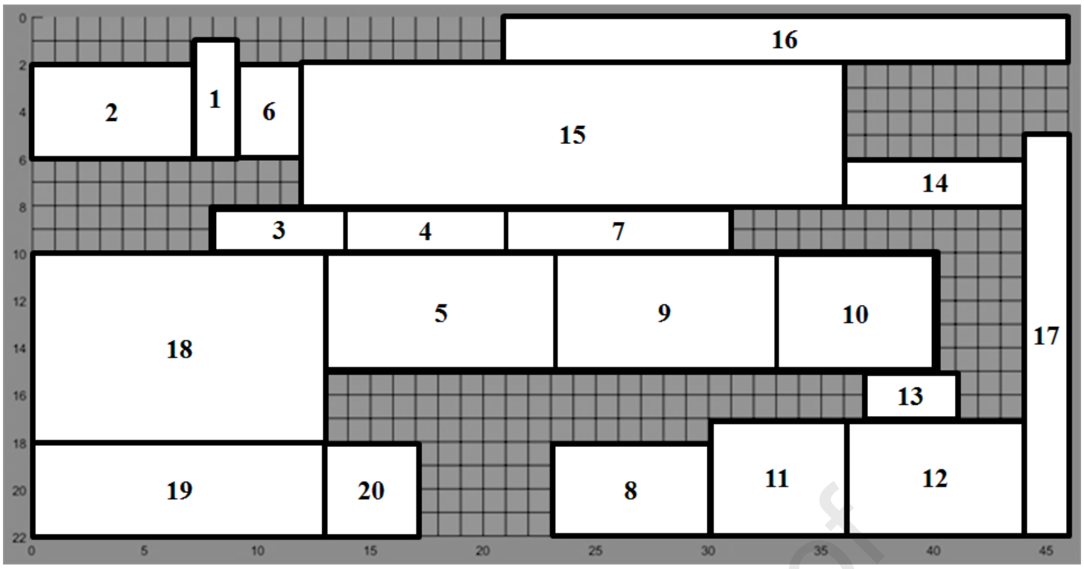

Figure 14. SGAELS (Scenario 1 - 2nd Stage)

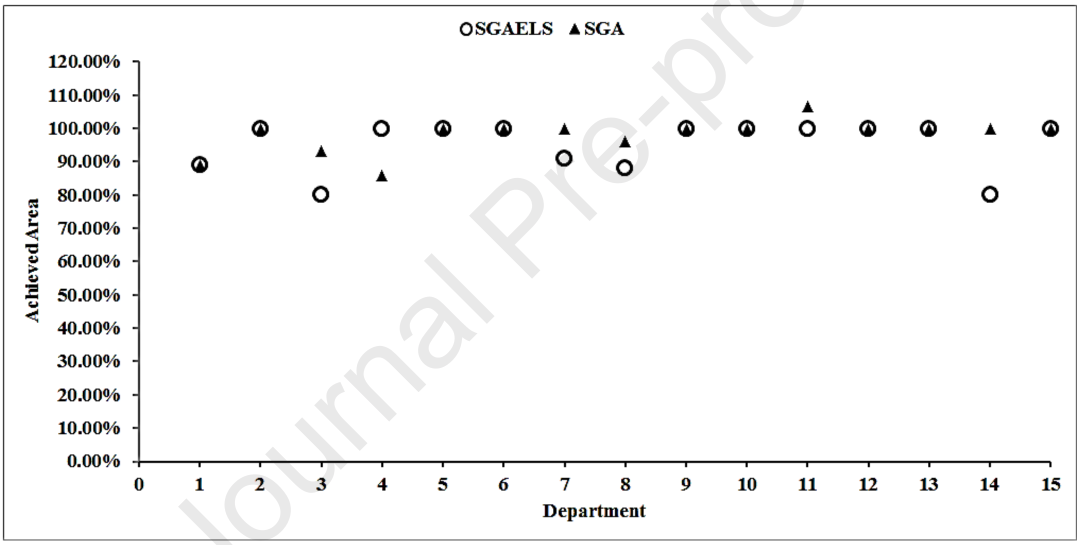

Figure 15. SGAELS vis à vis SGA (Scenario 1 - 2nd Stage – Achieved Area)

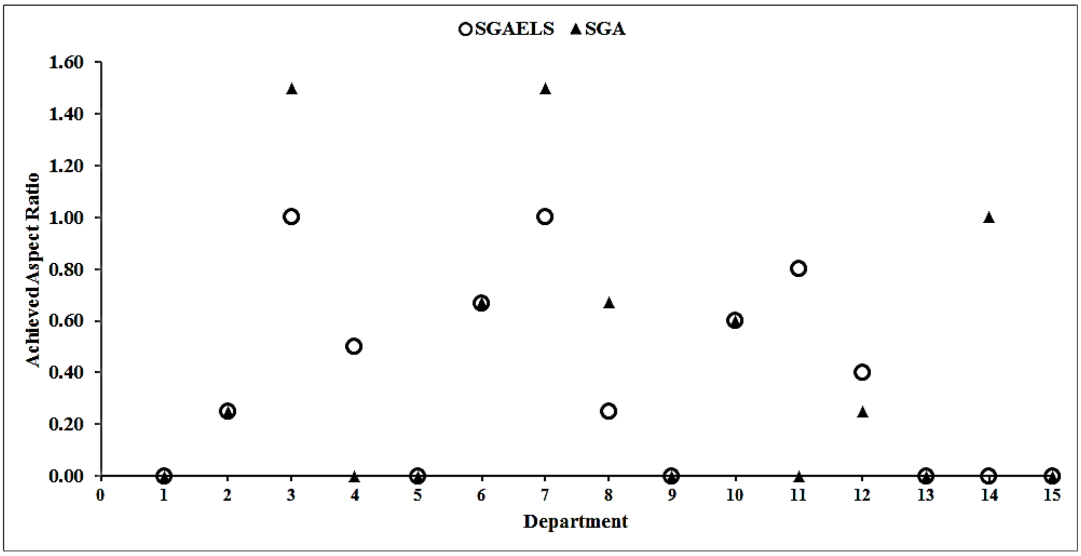

Figure 16. SGAELS vis à vis SGA (Scenario 1 - 2nd Stage – Achieved Aspect Ratio)

Figure 17 shows the layout configuration achieved by the SGAELS, scenario 2. The configuration becomes optimized due to less distance between departments, according to Table 11.

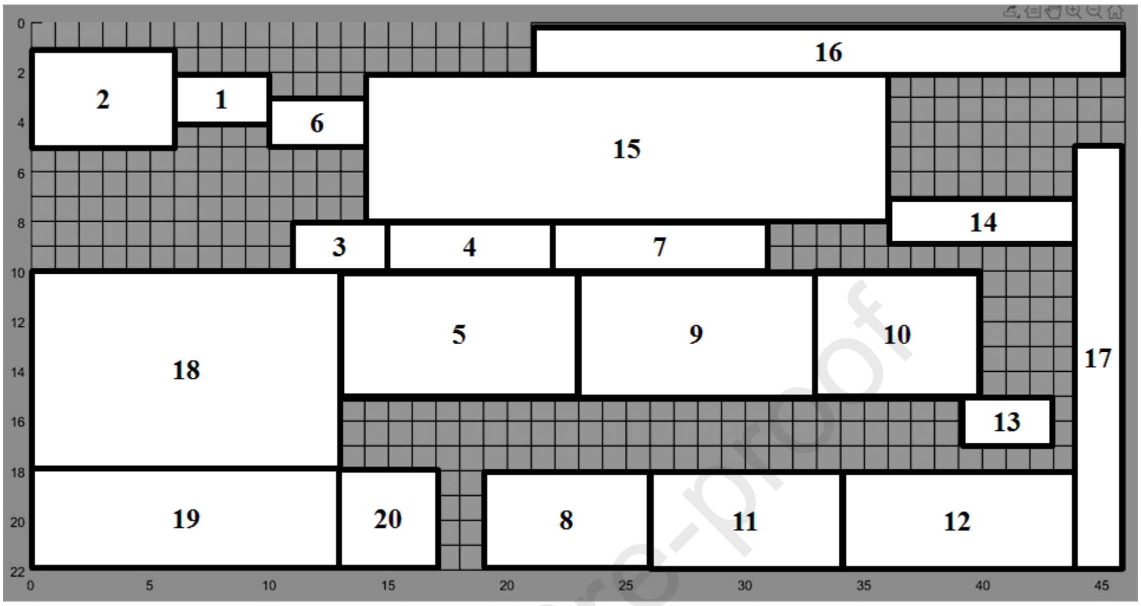

Figure 17. SGAELS (Scenario 2 - 2nd Stage)

In the 2nd scenario (Figures 18 and 19) the pattern repeats itself: seven departments obtained inferior satisfaction, only 1 obtaining a better answer, while 3 could match the ideal aspect, 2 obtaining a better answer than [2] even though not ideal, and only 3 deviating from the objective.

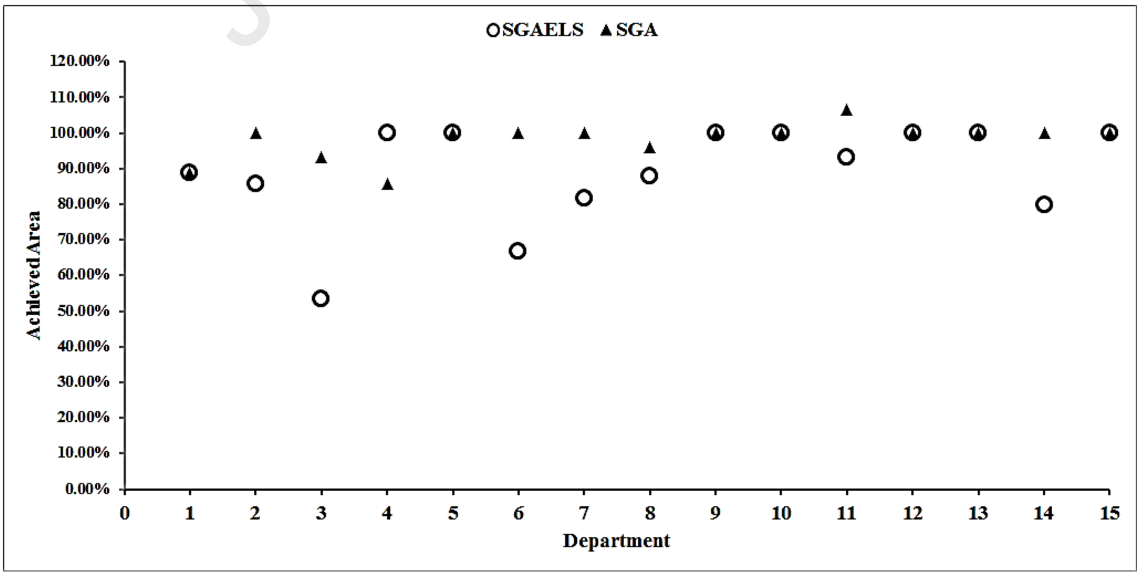

Figure 18. SGAELS vis à vis SGA (Scenario 2 - 2nd Stage – Achieved Area)

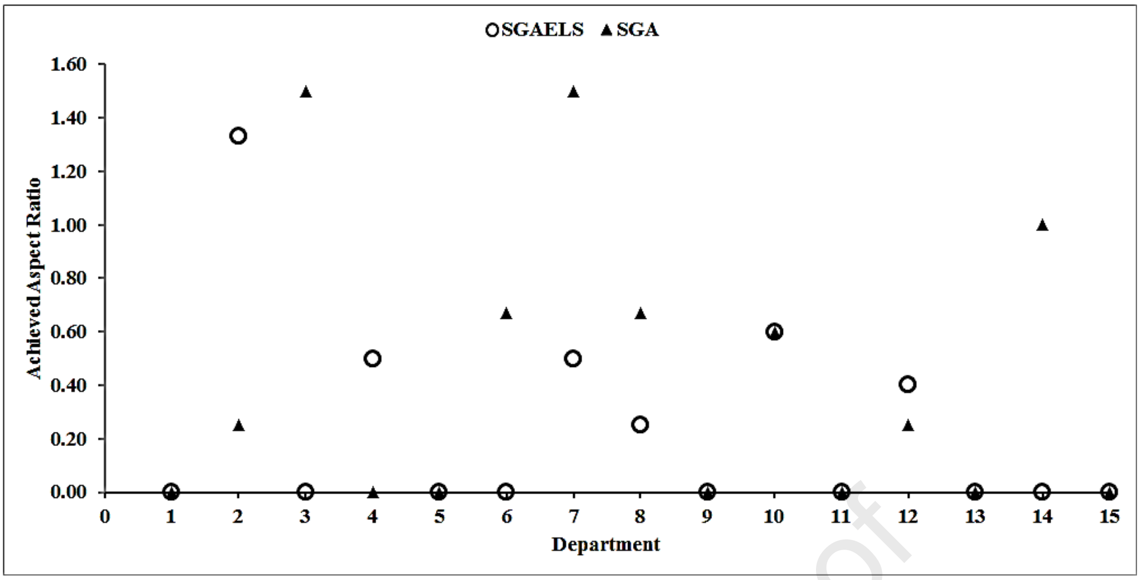

Figure 19. SGAELS vis à vis SGA (Scenario 2 - 2nd Stage – Achieved Aspect Ratio)

As described above, every iteration of a department is selected using the roulette method, based on the probability values of the mathematical expression (19) for each department.

The stochastic–growth–based process, gives geometric shape departments selected after a determined number of iterations and, accordingly, at the end of an optimization process gives shape to the layout when a good solution found. Figure 20 shows the number of iterations required for convergence of centroid coordinates distributed on a geometrical grid, as indicated in Figure 5, in an optimal layout that satisfies the required size and aspect ratio of each department as indicated in Figures 14 (scenario 1) and 17 (scenario 2).

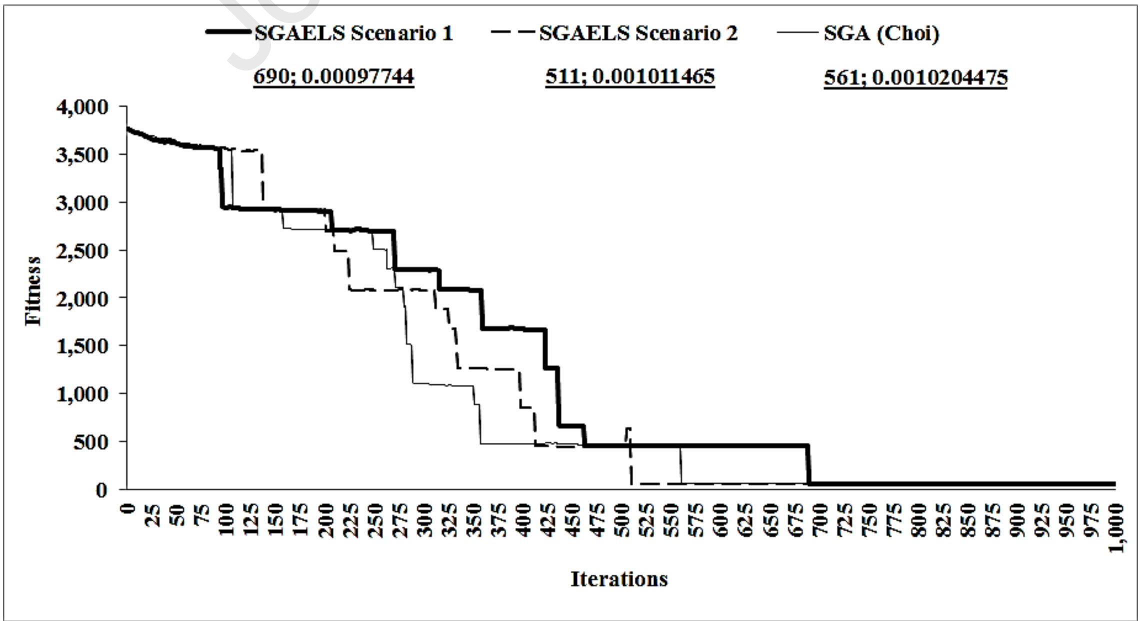

Figure 20. Convergence graph: SGAELS vis à vis SGA (Scenarios 1, 2 and [2])

For comparison purposes only, SGA has been executed and a layout similar to the layout proposed by [2] was selected (see Supplementary Material (Sections B, C, and D).

According to Figure 20 the SGAELS, in the case of scenario 2, defined the layout planning after 511 iterations with the TMHC value equal of 101146.5 (see Supplementary Material (Section C)).

5. Conclusion

Facility Layout Planning strongly impacts productivity and efficiency of industrial operations due to all the problem variables (such as manufacturing and material handling costs, production flow synchronism, production time, and distance travelled by complete/intermediate products) varying significantly, in a positive or negative way, depending on the quality of the decision-making during layout planning. Therefore, in this context, the proposed stochastic optimization process demonstrates competence on solving shipyard facility layout problems.

In 1st stage the scientific contribution of the work is based on the use of the partial mapping technique and the recursive algorithm applied to the genetic procedure proposed in this work. As a result of the proposed procedure, in the 1st stage should be noted that with only 100 iterations the minimum cost of 11,489 units was obtained, while the procedure proposed by [2] reached the same minimum cost with 3740 iterations.

[94] corroborates the validation of what was developed and presented as a research result of this work. According authors, generally speaking, Genetic algorithms demonstrate, in most applications, superior performance when compared to other heuristic methods due to being parallel processing algorithms: using multiple-points in the search of the solution space. Such characteristic increases the opportunity of reaching the global optimal solution without falling into local optimal solutions in the vast majority of problems addressed, leading them to be considered a robust approach for accompanying artificial intelligence.

In 1st stage should be noted that keeping department 3 in position 5 of the topological Grid, the result obtained is a cost equal to 10,944, the same cost found in [16] work. In this case, Department 3 represents the beginning of the shipyard´s production flow and the entrance to the land is on the left side and in the upper part of the Grid, which is incongruent with regard to the positioning of the Department and for this reason, the result of the distribution of departments on the Grid corresponding to the cost of 10,944 was discarded in this work.

Other scientific contribution is based on the use of the Algorithm of Transition Procedure, domain change of the departments' centroid coordinates from the topological grid (discrete representation) to the geometric (continuous representation). Transition Procedure Algorithm (TPA) contributes towards reducing computational time when solving the 2nd stage.

From results of the topological optimization, the department centroid coordinates are transferred to the shipyard land grid by a centroid coordinates transfer procedure, which considers the 1st stage closeness constraints (alignment–and/or–adjacency–conditions–based), in addition to area constraints and the relation of aspect required of each of the departments.

Finally, a stochastic growth algorithm plus the electre methods and a local search method (SGAELS) represents another scientific contribution of this work. Electre method involves a group of decision-making methods that allows an individual, or algorithm, to choose an action from a group of possible actions. For this purpose, a weighting system is created, defining a hierarchy of importance among the available actions.

The system applied in the algorithm dynamically defines the weight of each constraint, in order to balance it with the need for the solution. If, for example, a currently running solution respects more position constraints than approximation constraints, the algorithm will adapt the weights so that the position constraints receive proportionately more attention [22,84,95]. The stochastic algorithm plus the electre methods has a reduced execution time but tends to achieve global optimal results less frequently. Local search engines applied increase their efficiency. At the end of the execution of the stochastic algorithm plus the Electre method, if there are departments that did not meet some proximity constraint, the local search engines are executed. This algorithm, positions centroid coordinates of each of these departments are explored, modifying their positions (when possible) to bring them closer to the departments with which they have incomplete constraints.

This process is done to respect the area limits provided, as well as the constraints previously reached, making it impossible for the new result to be inferior to the one presented by the stochastic algorithm plus the electre methods. Local search engines look for continuous improvement over some initial solutions to obtain better solutions.

The local search procedures are incorporated with other algorithms to further improve their performance [96]. Our work has been outstanding in this respect, a considerable reduction in the penalties assigned value in mathematical expression (12) based on a proposed scheme to solve the problem was achieved.

The result demonstrates that in the case of scenario 2 the SGAELS terminated the optimization process earlier. Also, the new proposed algorithms show themselves to be best suited to achieve the correct dimensions and aspect ratio of the departments while attending cost value.

With this result, we realize that SGAELS allows the departments to gradually grow and stay ordered according the pre-determined requirements from design decisions, once the continuous representation modeling approach that developed was capable of controlling and adjusting dynamically the stochastic– growth–based process of areas of the layout´s departments without prior calibration.

The Electre and local search methods do not allow significant deviations from the department´s centroid by performing cyclic adjustments during geometry optimization, while making the respective geometries satisfies given requirements in area, closeness constraints (adjacency–and/or–alignment–conditions–based), and shape reducing consequently the computational time during the simulation scenarios.

The decision of developing the SGAELS with the proposed control and adjustments as a solution for the stochastic–growth–process is justified by analysis of the better results achieved by this work.

Declarations

Author contribution statement

Azzolini W. J.: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Azzolini F. G., Mundim, L. R., Porto A. J. V., Amani H. J. S.: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

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Data availability statement

Data included in article/supplementary material/referenced in article.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: