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[191003] Method to integrate the microbusinesses from the textile sector in Bogota based on an association and allocation approach

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Abstract

Association among microbusinesses is a strategy to achieve common objectives, as it helps to consolidate some business operations in the marketplace. Association provides the opportunity to strengthen their capabilities and share resources without merging. However, in some cases, the process to create a productive association is done under the criteria and experience of each organization, rather than on a quantitative tool for decision-making. Therefore, this study develops a method, implemented in the computational tool Visual Basic for Applications, based on a genetic algorithm, involving the weighting of multiple criteria through AHP, that organizes microbusinesses into business clusters, and dispatching rules to allocate production and tasks within the associates (intra-cluster and inter-cluster). The results obtained by the association stage of the heuristic are validated against simulations performed using the mathematical model for association, and a good cluster conformation is observed. The performance reached in the allocation stage of the method and the subsequently scheduling are evaluated in comparison with the optimal solution provided by the mathematical model for general allocation and with the performance measures for allocation inside the cluster, respectively. The solution targets efficient and balanced production order distribution among the microbusiness clusters. In this paper, is presented the application of the method to a case study of informal sewing workshops located in Usme, Bogota (Colombia).

Keywords: business association, microbusinesses, production allocation, quantitative method, business clusters, genetic algorithm, AHP, scheduling, hybrid method, mathematical model, textile sector

1. Justification and approach to the problem

In Colombia the 51.1% of the population corresponds to be the base of the pyramid (BoP) (World Bank, 2019). The people who belong to this proportion, in most cases, work in informal activities (DANE, 2018). Some of these activities take place in handicraft workshops, family businesses and mothers-head-of-household businesses. Under the Colombian classification, these businesses belong to a category named microbusiness (0-10 employees). This category includes informal businesses, which have shown difficulty participating in the marketplace. A way to overcome these difficulties and achieve business growth, could be by becoming part of a supply chain of an anchor company as either suppliers, consumers, retailers, employees, or entrepreneurs of different types of products (Golja, 2012). In this context, the inclusive business model is a strategy promoted by anchor companies that "seek to contribute towards poverty alleviation by including lower-income communities within its value chain while not losing sight of the ultimate goal of business, which is to generate profits" (Jenkins & Ishikawa, 2010).

The inclusive business model not only brings the opportunity to earn higher incomes to people involved in them, but also offers new ways for innovation and growth, and represents a competitive advantage for the microbusinesses, generating a social and development impact at the same time (Jenkins & Ishikawa, 2010; Bonnell & Veglio, 2011). However, the process for a microbusiness to become an inclusive business represents a challenge, thus, to achieve this challenge is advisable to make associations. By doing so, association among microbusiness allows the combination of complementary and compatible resources, increasing their capability to participate in the supply chain as suppliers and to absorb the production order from the anchor company. By joining forces, it is more likely for microbusinesses to be able to absorb the demand from the anchor company and improve their production and logistics processes (Zambrano, López, Fiorillo, Lazo, Molina & Guzman, 2019).

The association must be coordinated, distributing the tasks in the best way subject to the characteristics of each associated business. As is mentioned by Cheng, Ioannou and Serafeim (2014), in order to be viable, it is necessary to create an organization structure, named cluster, that will allow the association to supply the production order, being economically feasible for its members and at the same time economically, environmentally and socially sustainable.

Padmore and Gibson (1998) define a cluster as “a concentration of businesses that interact, whether that is through competition, cooperation, or by serving as suppliers or customers in the value-chain". According to this and other published studies, clusters are considered to be tools that can be used to accelerate innovation, cooperation among actors and contribute to the economic and competitive development of businesses in the global market. It is emphasized that business clusters are more productive and competitive than non-cluster businesses, due to their greater flexibility, faster speed of reaction and a broader set of opportunities available to them for action (Østergaard & Park, 2013; Marting & Sunley, 2003). An interesting aspect about clusters is that they promote competition and cooperation. The cluster members compete together to win and retain customers. There is also cooperation involving companies in common industries and local institutions (Porter, 1998).

Some of the case studies presented in the literature about industrial clusters propose to build them based on association criteria as inventory capacity, production rate, product quality, lead times, location, transportation and purchasing costs. Even though the documented studies assess cases in which firms are of more than 10 employees, it is expected that the results founded also apply to microbusinesses. The previous statement is reasoned, based on the fact that smaller companies have bigger opportunities to solve their weaknesses by association (Dana, Granata, Lasch & Carnaby, 2011).

According to the context described above, it was found that traditional quantitative association techniques aim to reduce the difference among businesses that conform a certain cluster, in relation to the criteria, that are the variables inserted in the analysis. Overall, associations among microbusinesses are done by qualitative or empirical methods. In addition, there are few studies focused on quantitative methods that support the association of microbusinesses and the allocation of production (duties or tasks) within them, considering different association criteria. A method based on an association and allocation approach is expected to conform competitive clusters, capable of complying production orders and assigned duties, as well as improving their income. Additionally, if it is possible, the method will facilitate the entry of the microbusinesses into a supply chain of an anchor company and simplify the process of becoming inclusive businesses.

2. Background

This section presents some works that review similar problems from both businesses association into clusters and allocation tasks among the businesses that conform the clusters.

Association

In related literature, several authors have carried out studies on associate businesses. A common approach is the formation of clusters. Conventionally, the clusters are the result of a self-selection process on the side of businesses, resulting in the advantage of exploiting their interdependencies for mutual benefit. According with Almeida and Kogut (1997) the conditions in which clusters generally emerge are shaped by geographical and relational proximity. When proximities are stronger, the information exchange, the share of common labor markets and the diffusion of knowledge, are more feasible, especially the diffusion of 'tacit' knowledge, which is difficult to document. On the other hand, Padmore and Gibson (1998) point out that clustering emerges in the function of the number and quality of linkages among businesses. Linkages stick an industrial cluster together and occur in any dimension: historical, commercial, jurisdictional, technological, geographical and social. In consequence, businesses make choices, either intentional or inadvertent, about how and with whom to cluster.

An example of qualitative industrial clustering is presented in the study carried out by Jimenéz, Medina, Schekaibán and Faride (2013). The purpose of the study is to analyze the importance of different criteria in the conformation of four industrial clusters in Tamaulipas, México based on in-depth interviews with members and participants. The findings suggest that geographic position and the sociocultural identity among cluster firms are two important criteria considered by the managers. Moreover, the internal networks are an important engine in clusters and are reflected in joint storage, shipping of raw materials, joint training and benchmarking. Even though this is a qualitative study, it contributes to the understanding of clusters that emerged naturally and the criteria that may have led to their successful performance. In this manner, natural clusters provide a framework to raise quantitative strategies for clustering.

Many different approaches are available to conform quantitative clusters, but according to Punj and Stewart (1983) the most common clustering algorithms can be classified inside the partitioning and hierarchical categories. Partitioning-based algorithms divide data objects into some predetermined number of partitions, where each partition represents a cluster and each cluster must contain at least one observation and each observation must belong to exactly one group. Observations are then reassigned to clusters until some decision rule terminates the process (Frunza, 2016). Examples of partitioning-based algorithms are: K-means (Kant, Mahara, Jain, Jain & Sangaiah, 2018; Kusrini, 2015), and fuzzy c-means (Kuo, Lin, Zulvia & Tsai, 2018). Hierarchical-based algorithms allocate the data set in a hierarchical manner "through a series of steps that build a tree-like structure by either adding individual elements to (i.e., agglomerative) or deleting them from (i.e., divisive) clusters" (Ketchen & Shook, 1996). Examples of hierarchical-based algorithms are: single linkage (Ros & Guillaume, 2019), complete linkage (Biggio, Bulò, Pillai, Mura, Mequanint, Pelillo & Roli, 2014) and Ward's minimum variance method (Eszergár-Kiss & Caesar, 2017).

An important choice required in clustering is the objective function or functions. Jamal and Montemanni (2018) formulate a single-objective clustering which enables the exchange of byproducts between dissimilar industries, taking advantage of the fact that resources needed by a production process could coincide within the waste of another production process performed by a different industry. The clustering is done through linear programming models, that maximize the profit derived by the exchange of byproducts and guarantees its fair distribution among the clusters. Sağlam, Salman, Sayin and Türkay (2006) presented a mathematical formulation for the clustering problem with the objective function of minimizing the maximum cluster diameter. The resulted model, called by the authors the MIP-Diameter model, because is a mixed-integer programming model (MIP), is applied to solve a clustering problem in the context of digital platform industry.

Further, the advantage of using quantitative strategies is the inclusion of more than two dimensions for sorting businesses into clusters. This approach is known as multi-objective clustering. Bowerman, Hall and Calamai (1995) assess this topic by solving the urban school bus routing problem. The authors group students into clusters under the restriction of a specific maximum walking distance (from a student´s home to a bus stop). Following this a school bus route is generated for each cluster, while maintaining equity among the group of distances student-bus stop. Conversely some authors approach multi-objective clustering by implementing clustering algorithms along with systematic techniques for weighing variables. Azadnia, Saman, Wong and Hemdi (2011) include fuzzy c-means with AHP (Analytical Hierarchy Process) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) for clustering customers under various criteria related to CRM strategies. Similarly, Azadnia, Ghadimi, Saman, Wong and Sharif (2011) use a fuzzy c-means for grouping suppliers and then rank them in each cluster by using ELECTRE (Elimination Et Choix Traduisant la Realité).

Allocation

Once the clusters are shaped, the microbusinesses that are part of them must use a methodology for the structuration of the duties to supply the production order. The general way founded for the organization and conformation inside the clusters is based on mixed linear programming algorithms. It includes parameters as: costs, experience, production rates, CSR topics, quality, lead times, location and budgets. This lead us to multiple-criteria decision-making problems (MCDM), which can be solved by using Analytical Hierarchical Process AHP (Mafakheri, Breton & Ghoniem, 2011), Technique for Order Preferences by Similarity to Ideal Solutions TOPSIS (Arabzad, Ghorbani, Razmi & Shirouyehzad, 2015) or Elimination Et Choix Traduisant la Realité ELECTRE (Covas, Silva & Dias, 2013). The authors mentioned above employed these techniques to obtain weights for different criteria and subsequently rank suppliers, allocate production orders or arrange plant layouts.

Returning to specific findings about order or tasks allocation among the cluster members, a study developed by Gaballa (1974) proposed a mathematical programming system to provide results for quantity orders of equipment and other items for the Australian Post Office. The objective of this programming system is the allocation of the total amount of orders at a minimum cost, among factories. This includes evaluating the economic costs of maintaining inefficient factories in the business, the discounts according to the amount of the orders, as well as considering the different production and capacity levels in the restrictions. The short time taken by this system to allocate orders gives manufacturers ample time to plan and prepare their production runs.

A considerable amount of literature has been published on solving this issue through mathematical models. These studies consist in a single objective function problem and usually consider criteria as delays, purchasing costs, transportation costs, lead times, production costs and quality. For instance, Torres, Rosas and Cruz (2012) determine if a supplier is selected or not and allocates a proportion of the total demand for the selected ones, under two scenarios: when the suppliers have the same features and when not. Another useful approach to the problem are intelligent hybrid models (mathematical model and heuristic), which are applied by Chen and Pundoor (2006) to a manufacturing company of short life cycle products. They found that some cases lead to non-deterministic polynomial time (NP) hard problem, leading to the design of fast heuristics for generating near-optimal solutions. These results reflect those of Che and Wang (2008) who also construct a mathematical model, a heuristic and even a Genetic Algorithm to solve the allocation problem. The authors take into account different production workloads and production periods. For comparing their solutions, they use the Lingo software package and show that their results are reliable and ready for practical applications.

An extension of the order allocation among suppliers may include various objective functions. This is assessed by Guo, Wong and Leung (2013), whom applied a model for solving the well-known MOAP (multiple objective assignment problem). It is developed with a MOMO (Multi-objective memetic optimization) process and minimizes three important and commonly used production objective functions: minimizing the total tardiness of all orders, the total throughput time of all orders, and the total idle time of all production departments. For validating results is included a Monte Carlo simulation technique, a heuristic pruning technique and a Tabu search, for providing Pareto optimal solutions. Experimental comparisons showed that the method is effective and provides quality results.

After a detailed investigation about association and allocation methods, we could identify prior and useful studies around these issues. It is concluded that a promising way to conform microbusinesses clusters is by building a quantitative method joining business association and order allocation (inter and intra cluster). Along with this strategy we aim to involve some abovementioned criteria and in the case in which is likely to be in front of a NP-hard problem, we will consider including not only mathematical modelling and quantitative techniques but also heuristics and metaheuristics.

3. Objectives

Develop a quantitative method in order to conform microbusinesses clusters and allocate production orders among the microbusinesses that belong to these clusters, and test it through a case study in the textile sector.

• Identify and quantify the association criteria relevant for microbusinesses from the textile sector.

• Design a quantitative association-allocation method that determines the association of microbusinesses into clusters and the allocation of production orders among them.

• Validate the viability of the proposed method by making use of a case study in the textile sector.

4. The association-allocation method

The main design of this work is an association-allocation method implemented in the computational tool Visual Basic for Applications (Appendix 1), in order to group microbusinesses through clustering and production allocation techniques. The key feature is that both stages, association and allocation, are integrated in a hybrid method, although here there will be explained separately. This section is outlined as follows. First, in sub-section 4.1 is addresses the pseudo code of the method. Then, in sub-section 4.2 and 4.3, is treated the association and the allocation stage respectively, and in each one appears the preliminaries aspects to board the association/allocation problem, a proposed mathematical model to solve it and the heuristic solution which was chosen for the method. Afterward, sub-section 4.4 provides the tests used to proof the performance of the method. Finally, sub-section 4.5 is dedicated to the case study and simulated scenarios.

4.1. Pseudo code

The pseudo code, in the Figure 1, illustrates the integration of multiple criteria for association of microbusinesses into clusters and subsequently the allocation of production orders inter and intra cluster. Firstly, there is a reading of data, corresponding to the directory of microbusinesses, products, machines, geographical and relational proximity, and tasks, which is required for calculating the differences between microbusinesses, named distances. After this the AHP weights, previously calculated, are assigned to each criterion, this allows the subsequently calculation of the total distance for each pair of microbusinesses. Then the next reading of data is executed, this includes, the roadmap for manufacturing the products, willingness to produce certain products, processing times and production orders. Also, the values for the standard times and for the parameters of the Genetic Algorithm are obtained.

Consecutively, is started a cycle for testing each number of feasible clusters, in which a genetic algorithm is done to integrate a specific number of clusters, according to the index iterationK. The best association solution is selected and constitutes the input for the allocation methodology, which allocates the production among the clusters and then programs the scheduling for each cluster. At last, there is an association-allocation output for each iterationK, so in order to select the best solution, it is selected the minimum makespan across the results.

```
Read user data
Calculate Distances
        | Assign AHP weights to criteria
        | Standardization of each criterion
        | Calculate total distance between each pair of microbusinesses
Read for allocation
        | Read Processing times per company, task and product
Calculate standard times
Read microbussinesses data
        | Define population, generations and mutation probability
For iterationK =2 to TotalMicrobusinesses/2 do
        | Connection
        |       | Genetic algorithm
        |       |       | Genetic
        |       |       |     Initialize population
        |       |       |     For b=1 to generations do
        |       |       |           | One point crossover population
        |       |       |           | Mutation
        |       |       |           | Verify the number of clusters on the chromosomes
        |       |       |           | Replace parents for children
        |       |       |           | Fitness
        |       |       |           |     Sum of distances between microbusinesses for each cluster
        |       |       |           |     Save the minimum sum of distances
        |       |       |           | Save best chromosome
        |       |       |           |     Choose the maximum objective function
        |       |       |     End For
        |       |       | Best K
        |       |       |     Save best individual across generations
        |       | General Allocation
        |       |       | Order allocation among clusters
        |       | For CurrentCluster = 1 to iterationK do
        |       |       | Attribute standard times to engaged microbusinesses
        |       |       | Do
        |       |       |     Scheduling (CurrentCluster)
        |       |       |           Select available operations with minimum time
        |       |       |           Select the best machine for each operation
        |       |       |           Select pairing (operation-machine) with minimum time
        |       |       |           Allocation
        |       |       |                Allocate selected pairing
        |       |       |                Update times
        |       |       | While non- assigned operations > 0
        |       |       | Save indicators for each machine
        |       | End For
        | Save scheduling and objective function for each cluster
End For
Select best iterationK with minimum makespan
```

Figure 1. Pseudo code.

4.2. Association

The association stage lies in organizing microbusinesses into business clusters. The goal is to build integral clusters, which means a fair distribution of microbusinesses among them. First, relevant criteria are selected to characterized the microbusinesses. Also, a weight is assigned to each criterion, that corresponds to its importance according to the judgements of the experts collected through the application of the AHP technique. Then the criteria are quantified for each microbusiness and turned into distances in relation with the other participants of the association. Lastly, the distances are the input of the algorithm that is applied to finally obtain the clusters. The details are explained below.

4.2.1. Criteria and AHP

The knowledge of the people working on the microbusinesses located in Usme, the case study, is crucial because they own the practice and experience on the field. Currently, there are not historical records about criteria to associate microbusinesses from the textile sector, therefore it was collected through a literature review and surveys. These surveys were applied not only to these microbusinesses but also to some textile companies, via phone call or group meeting (Appendix 2 – Sheets A to D).

The criteria selected include both categorical and quantitative variables. Its definition and quantification along with its measurement units is presented as follows:

Criteria	**Variable type**	**Units**	**Definition**
Geographical Proximity	Quantitative	km	Geographical distance between microbusiness
Relational Proximity	Categorical	binary	Willingness to work together between microbusinesses
Products	Categorical	binary/type	Products manufactured by each microbusiness
Machines	Quantitative	machines/type	Machines owned by each microbusiness

Table 1. Criteria, variable type and units.

According to Almeida and Kogut (1997) geographical and relational proximity are essential for the formation of clusters. Moreover, based on the literature is known that “some enterprises had established collaboration connections between different suppliers in order to develop advanced products adapted to specific needs of their customers. Also, this configures competitive advantages accounting for knowledge sharing, new products and best practices” (Capó-Vicedo, Expósito-Langa & Masiá-Buades, 2007). Therefore, the products manufactured by the microbusinesses are selected as a criterion for the association. The last criterion, machines, constitute a feature of each microbusiness that contributes to the productivity of the cluster in the form of sharing sources and knowledge in relation with the execution of tasks. Additionally, references from experts identify the mentioned criteria as relevant for clustering analysis in the textile sector.

The weights of the criteria are calculated using AHP (Analytic Hierarchy Process), that solves multi-criteria decision problems. It considers all the categorical and quantitative variables that are needed to develop the association of the microbusinesses and measures its influence. This process applies the scale proposed by Thomas Saaty to assign a weight of influence based on the knowledge of experts (Guijarro & Guijarro, 2019). See Appendix 2 - Sheets E to G.

4.2.2. Distances

Afterwards the selection of the criteria, it is important to obtain a measure of distance between any pair of microbusinesses and for each one of the criteria. Each microbusiness must have a specific score in each criterion, so that the computing of the distance corresponds to the difference in between these scores of each criterion. For example, the criterion machines corresponds to the number of machines that an specific microbusiness owns, in this case the distance between the microbusinesses Oneyda Castañeda, which has 5 machines, and Clarita Rodriguez, which has 9 machines; is the difference in between them, that is to say 4 machines.

However, these values are not comparable because the measurement units between criteria have different scales. In order to get comparable scales and do not fall into biases on behalf of outliers, is used the normalization process applied by Azadnia, Mat Saman, Wong, and Hemdi. They use it for a min-max approach, which requires values in the range 0-1 (2011).

Relational proximity is already in this range, so the normalization is done for the rest of the criteria. The geographical proximity criterion is normalized using the following formula:

$$Criteria = \frac{Max\ Value\ of\ field - Value}{Max\ Value\ of\ field - Min\ Value\ of\ field} \quad (Equation\ 1)$$

For machines and products:

$$Criteria = \frac{Value - Min\ Value\ of\ field}{Max\ Value\ of\ field - Min\ Value\ of\ field} \quad (Equation\ 2)$$

Finally, the normalized data is weighted with the results of the AHP technique, and to obtain a general measure, the distances across all criteria are added for every pair of microbusinesses, the distance matrix is submitted in Appendix 3. These values will be used for quantifying a proxy of similarity between the microbusinesses and subsequently develop an algorithm to group the microbusinesses based on these distances. Figure 2 presents the flow chart of the calculation for the distances:

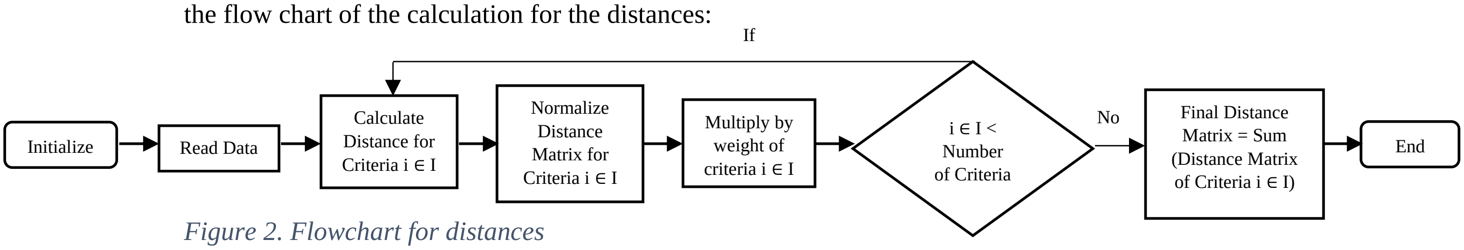


Figure 2. Flowchart for distances

4.2.3. Mathematical model

In order to make an optimal assignment of the microbusinesses to the clusters, a mathematical model of entire programming is formulated. The following definitions are considered:

Sets:

I = Set of all the microbusinesses
J = Set of all possible clusters to be opened

Parameters:

$Dist_{ik}$ = *Distance from microbusiness* $i \in I$ *to microbusiness* $k \in I$
$SumTot$ =*Sum of the entire matrix of distances between microbusinesses*
$ClustersAbrir$ = *Number of clusters to open in the association*

Variables:

$O_j = \{1\ if\ the\ cluster\ j \in J\ is\ open, 0\ otherwise$
$Y_{ij} = \{1\ if\ the\ microbusiness\ i \in I\ is\ in\ the\ cluster\ j \in J, 0\ otherwise$

$X_{ikj} = \{1\ if\ the\ microbusiness\ i \in I\ and\ the\ microbusiness\ k \in I\ belongs\ to\ the\ cluster\ j\ \in J,$
$0\ otherwise$
SDT_j = *Total sum of distances of the cluster* $j \in J$
Q = *Minimum sum of distances of a cluster*

Given these definitions, it is possible to formulate the following linear mathematical model to conform microbusinesses clusters.

Maximize = Q

Subject to:

$SumTot = \sum_{i \in I} \sum_{k \in I} Dist_{ik}$		(1)
$\sum_{j \in J} Y_{ij} = 1$	$i \in I$	(2)
$SDT_j = \sum_{i \in I} \sum_{k \in I} X_{ikj} * Dist_{ik}$	$j \in J$	(3)
$Y_{ij} \leq O_j$	$i \in I, j \in J$	(4)
$O_j \leq \sum_{i \in I} Y_{ij}$	$j \in J$	(5)
$\sum_{j \in J} O_j \geq ClustersAbrir$		(6)
$2 * X_{ikj} \leq Y_{ij} + Y_{kj}$	$i \in I,\ k \in I, j \in J \mid k \neq i$	(7)
$Y_{ij} + Y_{kj} \leq 1 + X_{ikj} * 1000000000$	$i \in I,\ k \in I, j \in J \mid k \neq i$	(8)
$Q \leq SDT_j + (1 - O_j) * 1000000000$	$j \in J$	(9)
$O_j \in \{0,1\}$	$j \in J$	(10)
$Y_{ij} \in \{0,1\}$	$i \in I, j \in J$	(11)
$X_{ikj} \in \{0,1\}$	$i \in I, k \in I, j \in J$	(12)
$SDT_j \geq 0$	$j \in J$	(13)
$Q \geq 0$		(14)

Constraint (1) assigns the value of the total sum of distances between the microbusinesses to the variable $SumTot$. Constraints (2) guarantee that each company must be assigned to a cluster and can only belong to one. Constraints (3) assign to the variable SDT_j the total sum of distances of the microbusinesses that are part of each cluster. Constraints (4) ensure that a microbusiness is not assigned to a cluster that does not open. Constraints (5) guarantee that if the cluster is opened, at least one microbusiness must be assigned to it. Constraint (6) guarantees that the number of clusters pre-defined are opened. Constraints (7) and (8) ensures that for each pair of microbusinesses the variable X_{ikj} takes the value of 1 if they are participating in the same cluster, and 0 otherwise. Constraints (9) keep the minimum sum of distances of a cluster. Constraints (10) through (12) are the integrality restrictions. Constraints (13) and (14) are non – negativity restrictions.

The mathematical model is compiled in GUSEK (GLPK Under Scite Extended Kit) (Appendix 4) with the matrix of distances from the case study. Graphic 1 shows the execution time to solve the model for two, three and four clusters. As it has an exponential behavior, is concluded that the association of microbusinesses is a NP-hard problem. Therefore, a genetic algorithm is built to provide a heuristic solution.

Graphic 1. Execution time to solve the association model applied to the case study for two, three and four clusters.

4.2.4. Genetic algorithm

First, a diverse initial population of randomized solutions is created for the clustering of microbusinesses. Individuals are recombined each generation to produce offspring that will be inserted in the next generation, and always is kept the best individual per generation. At the end, the best individual among generations is selected.

Chromosome encoding: The chromosome has as many genes as microbusinesses participating in the association. Every gene corresponds to a microbusiness according to its position. The first gene corresponds to the microbusiness with identification number (ID) 1, the second gene corresponds to the microbusiness with ID 2, and so on. In the gene appears a value between one and the number of clusters that are being built, and it refers to the cluster that the microbusiness is been assigned to. (Figure 3)

Chromosome:	1	3	1	2	2	3	1	2	3
Microbusiness:	ID 1	ID 2	ID 3	ID 4	ID 5	ID 6	ID 7	ID 8	ID 9

Figure 3. An example of a chromosome is presented, where nine microbusinesses are participating of the association and three clusters are being built. The microbusiness with ID 5, is represented by a gene in the 5th position from left to right, and has been assigned to the cluster 2, as it can be appreciated through the value that is consigned in the gene.

Fitness function: The aim is to build integral clusters that means a fair distribution of microbusinesses among the clusters, where the weaknesses and strengths of each other are compensated, different from a traditional clustering that groups elements by similarity. To quantify if clusters are integral, the heuristic sums the distances between the microbusinesses of each cluster. With this value per cluster, named SDT as in the mathematical model, it is possible to compare among clusters. If the SDTs are close values, the chromosome represents a way to organize integral clusters. In contrast, distant values are synonym of not integral clusters. Chromosome fitness, named Q, is the minimum of the SDT values that is wanted to be maximize to reach a fair distribution. (Figure 4)

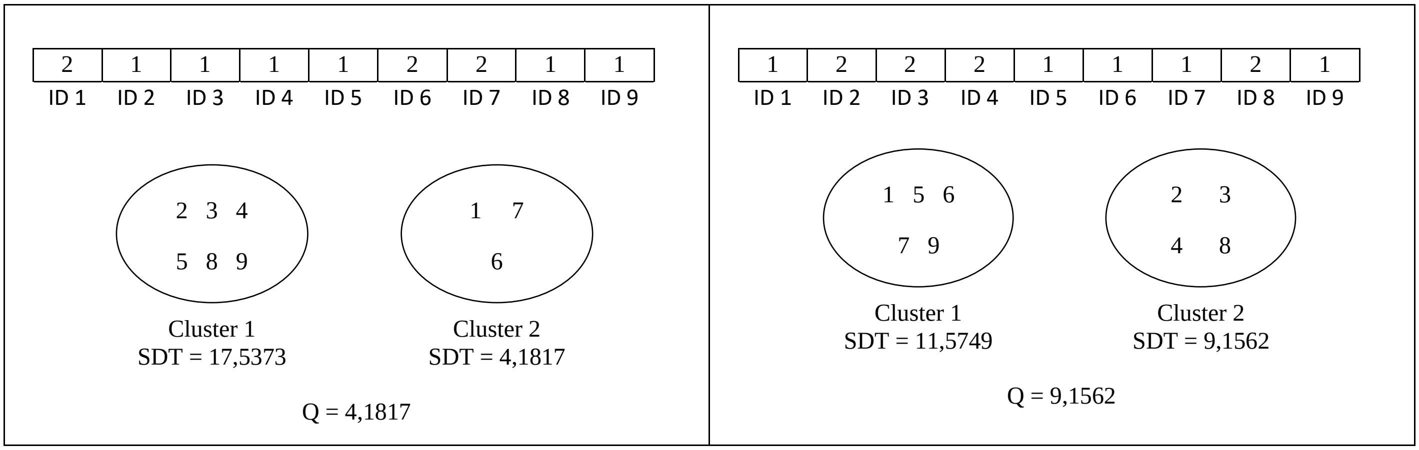


Figure 4. Two chromosomes are presented, both examples with nine microbusinesses participating of the association and two clusters. The panel on the left is an example of a bad distribution because the SDT values are distant from each other. The panel on the right is an example of a better distribution because SDT values are close. Finally, as the aim is to maximize the minimum of the SDT values, through the fitness function, the one on the right panel is selected as the best configuration between these chromosomes.

Crossover: It is a sexual and single point crossing, so per crossover is needed two parent chromosomes. These chromosomes are cut at a randomly chosen place, to have each one a head (the genes before the cut) and a tail (the genes after the cut). The tails are exchanged and in this way two new individuals are created.

Mutation: If mutation happens, two randomly chosen alleles of the child chromosome are exchanged.

Parameters: The parameters of the proposed genetic algorithm are define based on formulas found in literature. From Williams and Crossley (1998) is adopted that the population is the length of the chromosome (L) multiplied by four and from Greenwell, Angus and Finck (1995) is adopted that the probability of mutation is one (1) divided between the length of the chromosome. The only parameter that has not formula is generations. Therefore, this parameter was chosen after exploring different values of generations (Appendix 5), and concluding that convergence to a solution that maximizes Q is reached surely with two times the amount of the population as the value of generations. (Table 2)

Parameter	**Name**	**Value**
Population (chromosomes)	pob	pob = L*4
Mutation rate	Pm	Pm = 1/L
Generations	gen	gen = 2*pob

Table 2. Genetic algorithm parameters.

Once the clusters are shaped, the next step is to allocate production orders inter and intra cluster, that is covered in the following sub-section.

4.3. Allocation

The allocation stage has two parts. First the production order is allocated between the clusters. Then the tasks to complete the allocated production to each cluster are assigned to the microbusinesses of the cluster. The details are explained below.

4.3.1. Preliminaries

- Before is applied the association-allocation method, all the production orders have to be consolidated in one production order that is presented in Table 3.

Production Order	Units	Size of the lot
Bed sheets	456	46
Uniforms	36	4
Pencil cases	892	89
Suitcases	188	19
Jackets	482	48
Camibusos	253	25
Vests	456	46
Pants	87	9

Table 3. Production order. Per product, it has to be entered the total amount of units to be manufactured and the size of the lot.

- In order to calculate the cycle time for each product is used the task with maximum processing time which reduces the time of the whole production line and represents the bottleneck.

4.3.2. Mathematical model for allocation among the clusters

In order to make an optimal assignment of the production order of each product to the clusters created by the association model, a mathematical model of entire programming is formulated. The following definitions are considered:

Sets:

J = Set of all created clusters as a result of the association model
P = Set of all products that shape the production order

Parameters:

$OrdenesProduccion_p = Production\ order\ quantity\ corresponding\ to\ each\ product\ p \in P$
$BINHace_{jp} = \{1\ if\ any\ company\ in\ the\ cluster\ j \in J\ makes\ the\ product\ p \in P, 0\ otherwise$
$CapProduccion_{jp} = Units\ processed\ of\ the\ product\ p \in P\ by\ the\ cluster\ j \in J\ \ per\ hour$

It is important to highlight that the $BINHace_{jp}$ parameter is related to $CapProduccion_{jp}$, since if the cluster does not make a product, this parameter corresponds to 0. The capacity for each product per microbusiness is obtained by the inverse of the cycle time. The production capacity for each product per cluster is the result of the aggregated capacities of the microbusinesses belonging to the cluster.

Variables:

$X_{jp} = Quantity\ of\ the\ product\ p \in P\ of\ the\ production\ order\ to\ be\ assigned\ to\ the\ cluster\ j \in J$
$MayorTiempo_p = Greatest\ completion\ time\ for\ the\ product\ p \in P\ of\ the\ production\ order$

Given these definitions, it is possible to formulate the following linear mathematical model for the allocation of the production order to the created clusters.

Minimize = $\sum_{p \in P} MayorTiempo_p$

Subject to:

$\sum_{j \in J} X_{jp} = OrdenesProduccion_p$	$p \in P$	(1)
$X_{jp} \leq BINHace_{jp} * 1000000000$	$j \in J, p \in P$	(2)
$X_{jp} \geq BINHace_{jp}$	$j \in J, p \in P$	(3)
$\frac{X_{jp}}{CapProduccion_{jp}} \leq MayorTiempo_p$	$j \in J, p \in P \mid BINHace_{jp} = 1$	(4)
$X_{jp} \geq 0$	$j \in J, p \in P$	(5)
$MayorTiempo_p \geq 0$	$j \in J, p \in P$	(6)

Constraints (1) ensure that the production order is assigned in its entirety. Constraints (2) guarantee that the quantity of the product of the production order is only assigned to the cluster if it does the product. Constraints (3) guarantee that the cluster will be assigned at least 1 unit of the production order if it makes the product. Constraints (4) ensure that the variable $MayorTiempo_p$ keeps the greatest completion time of each product of the production order. To calculate the previous variable the $BINHace_{jp}$ parameter must be 1. Constraints (5) and (6) are non – negativity restrictions.

The mathematical model is compiled in GUSEK (Appendix 6).

4.3.3. Mathematical model for allocation among the microbusinesses of the cluster

In order to make an optimal allocation of the tasks required to elaborate the allocated production order in each cluster, a mathematical model of entire programming is formulated. The following definitions are considered:

Sets:

I = Set of all the microbusinesses that belong to the cluster as a result of the association model
P = Set of all the products that belong to the allocated production order of the cluster
T = Set of all the tasks required for the elaboration of the products
M = Set of all the machines required for the elaboration of the products

Parameters:

$OrdenesProduccion_p$ = *Production order quantity of the product $p \in P$*
$Tareas_{pt} = \{1\ if\ the\ task\ t \in T\ belongs\ to\ the\ the\ roadmap\ of\ the\ product\ p \in P, 0\ otherwise$
$TiempoEstandar_{pt}$ = *Standard time of task $t \in T$ to manufacture the product $p \in P$ (minutes)*
$BIN_{tm} = \{1\ if\ the\ machine\ m \in M\ executes\ the\ task\ t \in T, 0\ otherwise$
$BINAdicional_{im} = \{1\ if\ the\ machine\ m \in M\ belongs\ to\ the\ microbusiness\ i \in I, 0\ otherwise$

Variables:

$asignacion_{ipt}$ = *Quantity of the product $p \in P$ allocated to the microbusiness $i \in I$ to develop the task $t \in T$*
$TiempoMaquina_{tm}$ = *Time that the machine $m \in M$ works to complete the task $t \in T$ (minutes)*
$TiempoMaquinaTot_m$ = *Total operation time of the machine $m \in M$ (minutes)*
Y_{pt} = *Number of tasks $t \in T$ to manufacture the units of the product $p \in P$*

$Mayor$ = *Time of completion of the machine that more time is in operation*

Given these definitions, it is possible to formulate the following linear mathematical model for the allocation of tasks to the microbusinesses of the cluster.

Minimize = $Mayor$

Subject to:

$Y_{pt} = Tareas_{pt} * OrdenesProduccion_p \qquad p \in P, t \in T \quad (1)$

$Y_{pt} = \sum_{i \in I} asignacion_{ipt} \qquad p \in P, t \in T \quad (2)$

$\sum_{p \in P} asignacion_{ipt} * TiempoEstandar_{pt} = \sum_{m \in M} TiempoMaquina_{tm} * BINAdicional_{im} \qquad i \in I, t \in T \quad (3)$

$TiempoMaquinaTot_m = \sum_{t \in T} TiempoMaquina_{tm} \qquad m \in M \quad (4)$

$TiempoMaquina_{tm} \leq BIN_{tm} * 1000000000 \qquad t \in T, m \in M \quad (5)$

$Mayor \geq TiempoMaquinaTot_m \qquad m \in M \quad (6)$

$asignacion_{ipt} \geq 0 \qquad i \in I, p \in P, t \in T \quad (7)$

$TiempoMaquina_{tm} \geq 0 \qquad t \in T, m \in M \quad (8)$

$TiempoMaquinaTot_m \geq 0 \qquad m \in M \quad (9)$

$Y_{pt} \geq 0 \qquad p \in P, t \in T \quad (10)$

$Mayor \geq 0 \qquad (11)$

Constraints (1) define the variable Y_{pt} as the number of tasks of each type to manufacture the total amount of units of each product. Constraints (2) ensure that all tasks are allocated to the microbusinesses of the cluster. Constraints (3) keep in the variable $TiempoMaquina_{tm}$ the time that a machine spends in a specific task. Constraints (4) define the variable $TiempoMaquinaTot_m$ as the total operation time of each machine, that corresponds to the sum of the operation time in the tasks. Constraints (5) guarantee that if the machine does not do the task it is not assigned to it. Constraints (6) save the completion time of the machine that more time is in operation. Constraints (7) through (11) are non – negativity restrictions.

The mathematical model is compiled in GUSEK (Appendix 7). Graphic 2 shows the execution time to solve the model with different test scenarios (Appendix 8). As the scenario has more data, the execution time grows exponential, so it is concluded that the allocation of tasks is a NP-hard problem. Therefore, in the following sub-sections is provided a heuristic solution.

Graphic 2. Execution time to solve the mathematical model for allocation among the microbusinesses of the cluster applied to different test scenarios.

4.3.4. Heuristic solution for allocation among the clusters

The production order is distributed among the clusters by the following steps:

1. Considering the processing times (minutes/unit) per product per microbusiness, the heuristic turns these times into capacity (units/hour).
2. To calculate maximum capacity, it is evaluated how much units of each product are done in each microbusiness in 120 hours (15 days x 8 hours/day).
3. The heuristic sums the maximum capacity per product of the microbusinesses that are in each cluster, to consolidate the maximum capacity of each cluster per product.
4. The number of units per product allocated to each cluster is proportional to the capacity of the cluster in relation with the total capacity of the association for that product (Xiang, Song & Ye, 2013).

$$X_{jp} = \frac{CapProduccion_{jp}}{\sum_{j \in J} CapProduccion_{jp}} * OrdenesProduccion_p \qquad p \in P$$

The following section presents the allocation of tasks among the microbusinesses of the clusters.

4.3.5. Heuristic for allocation and scheduling inside the cluster

After a set of production orders is given to the cluster, it is done a scheduling for processing the assigned orders at each microbusiness belonging to the cluster. There is a set of jobs to be processed on a set of machines, each job comprises a set of tasks that must be performed on a different machine and in specified processing times. This is a JSSP (Job Shop Scheduling Problem), a classical operations research problem which is a NP-hard, so even for small instances such as the one of the case study an optimal solution cannot be guaranteed.

The flexible job shop problem is an extension of the JSSP that allows an operation to be processed by any machine from a given set of alternative machines, this means that parallel machines are allowed. In this case, the problem is similar to a FJSSP (Chaudhry & Khan, 2016).

The assumptions for developing this problem are:

- ✓ All machines are available at time t = 0.

- ✓ All jobs are available at time t = 0.
- ✓ Each operation can be processed by only one machine at a time.
- ✓ There are no precedence constraints among the operations of different jobs; therefore, jobs are independent from each other.
- ✓ An operation once started cannot be interrupted.
- ✓ Time to setup the machine for processing any operation is included in the processing time.
- ✓ Maintenance and reparation times are not included.
- ✓ Times for the same type of machines inside a microbusiness are homogeneous.
- ✓ Once an order completes its processing is delivered to its customer immediately without any transportation time or cost (Chen & Pundoor, 2006).
- ✓ There is the same number of workers as workstations.
- ✓ Each machine is only qualified to produce a subset of orders.
- ✓ Each product has its own sequence across the machines.
- ✓ The processing times are deterministic.
- ✓ A cluster cannot process more than one production order at a time.
- ✓ The lots sizes are input parameters.
- ✓ The production orders do not have prioritization.
- ✓ The algorithm is compiled each time a new production order is received.

There are two subproblems involved in the FJSSP, first a routing problem where it is selected a suitable machine among available ones to process an operation, second a scheduling problem where operations are sequenced on the selected machine to obtain a feasible schedule that minimizes a predefined objective.

The key of the association relies in the collaboration between microbusinesses to process the products inside every cluster. This is represented as the willingness that a microbusiness has to execute any task of a product that it is not made by them, even though having the corresponding requested machine, and therefore become able to help others to produce it inside the group. To estimate the processing times for these microbusinesses the heuristic uses the result of the mean of the processing times per product of the microbusinesses that indeed manufacture each product.

A scheduling is done for each cluster, it receives all the information of the microbusinesses which belong to the cluster and the production order assigned to them. The objective function corresponds to minimize the makespan which according to the review of flexible job shop scheduling techniques by Chaudhry & Khan highlight is a well-known performance measure used in most of the papers evaluated. Also, the minimum makespan, implies minimizing the total completion time required for all jobs (2016).

Although, the frequent techniques to approach this problem constitute evolutionary algorithms, heuristics and other hybrid techniques, some authors use dispatching rules for solving FJSSP. They find efficient solutions and reasonably good schedules with a single objective (Golenko-Ginzburg & Laslo, 2004; Liu & Zhang, 2005).

In order to reduce the computational time, the way developed to solve this problem is based on the algorithm for scheduling “non-delay” and some dispatching rules. The former method assures that a machine will never be idle if it is possible for it to be processing any job (Nahmias, 1999).

The scheduling algorithm executed uses static and dynamic (the ones that are updated after any operation is programmed) dispatching rules. These rules assign a priority to the list of operations required to complete a job and subsequently a product lot. An operation is integrated by a given task, of a specific lot, of a product. For programming a single operation of the entire list of available works the following steps are accomplished:

1. The first operations available are the ones which have all precedences tasks done or correspond to the first task of the route.
2. The operations available have a specific initial time, so only are pre-selected the ones with the minor time, therefore the nearest available.
3. For the list of selected operations, a specific machine is chosen. The machine is selected by SPT (shortest-processing-time), starting with the minimum processing time, and minimize the time an operation is finished.
4. The operation and its corresponding machine with the minimum completion time is selected and scheduled. In case of equal completion times, the selected pairing (operation-machine) will be sequenced following the order of their indices and maintaining the homogeneity of the machine's utilization levels (Chen & Pundoor, 2006).
5. After an operation is scheduled, the times of the respective product and the machine are updated, and the previous process is repeated.

The above steps are performed until the number of non-assigned operations left is null. The final solution will be represented as the chart in Appendix 9, it shows the order in which each operation is processed in the group of machines that belong to a specific cluster.

Each scheduling allows the estimation of performance measures, which are listed here below:

- The maximum time of completion among the products, which is the makespan of the cluster.
- The completion time of each product lot, and the total production order.
- The utilization level of the machines.
- The number of empty machines.

Last of all, the different schedulings (for each cluster) are kept and then the higher makespan of all clusters belonging to a specific iterationK is named as the objective function of the allocation problem. Afterwards, it is selected the solution (established by the clusters conformation and scheduling) with minimum objective function.

4.4. Performance of the association-allocation method

4.4.1. Association

To evaluate the performance of the genetic algorithm as a clustering method, is compared the outcome of the method with the ones of the mathematical model (sub-section 4.2.3) compiled in GUSEK. Additionally, the Gini index is used as a performance measure to evaluate the conformation of clusters (section 5).

These tests are done with the nine microbusinesses of the case study, when the number of clusters are two, three and four. The goal is to contrast how dissimilar the method shapes the clusters along with the approach described above. Is found that the shape of the clusters is different, as the mathematical model reaches the optimum and the genetic algorithm not, but these differences do not affect drastically the performance of the method.

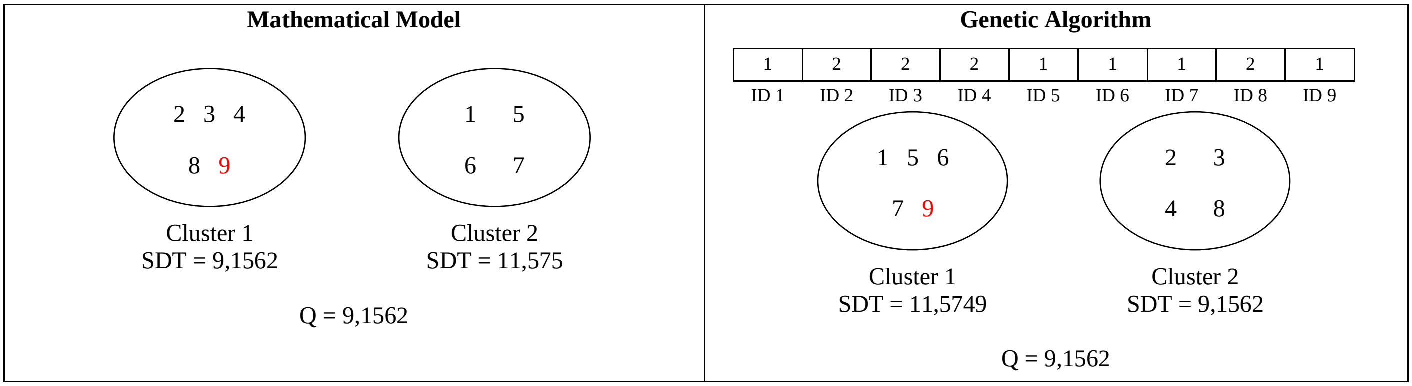


Figure 5. For two clusters, the genetic algorithm reaches the same Q of the mathematical model. The shape of the clusters is similar but not equal, the element that varies is the location of the microbusiness 9.

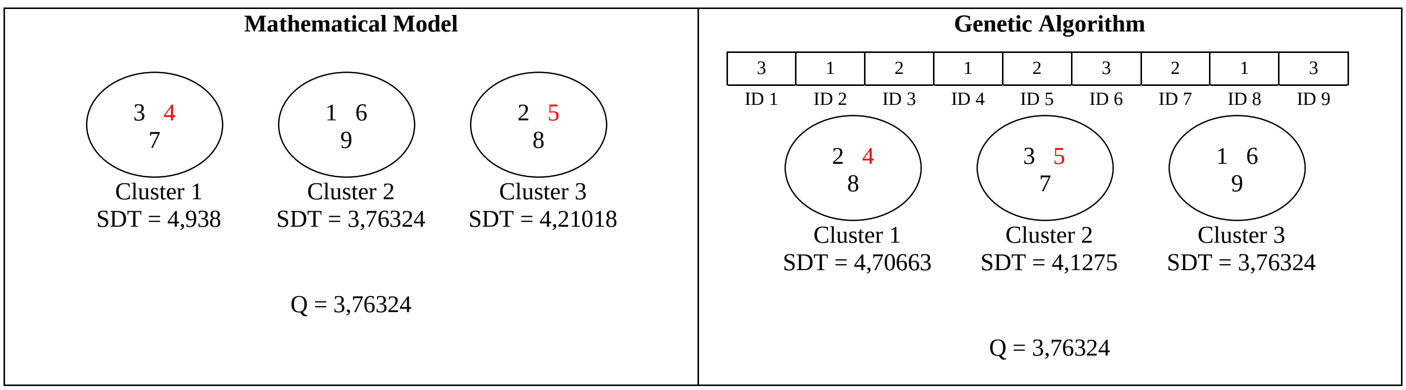


Figure 6. For three clusters, also the genetic algorithm reaches the same Q of the mathematical model. The shape of the clusters again is similar but not equal, the elements that vary are the location of the microbusinesses 4 and 5.

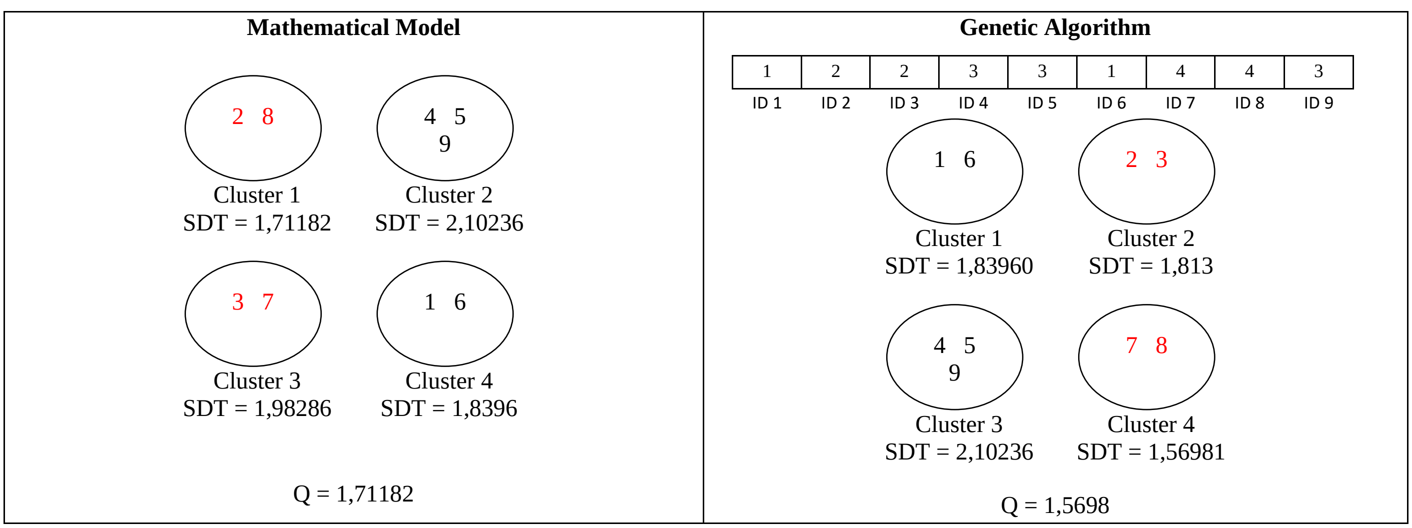


Figure 7. For four clusters, the genetic algorithm reaches a minor value of Q than the mathematical model. However, it is an acceptable value. The genetic algorithm shapes two clusters equal to the mathematical model, and the other two differ.

4.4.2. Allocation

In order to test the performance of the allocation among the clusters, the mathematical model presented in the sub-section 4.3.2 is compiled in GUSEK for two clusters, three clusters and four clusters. The results include the quantity of the production order for each product assigned to every cluster and compared to the allocations from the heuristic solution. The production order generated for the following tests correspond to the Table 3 and the microbusinesses correspond to the ones of the case study.

	Mathematical model		**Heuristic allocation**	
Products	**Cluster 1**	**Cluster 2**	**Cluster 1**	**Cluster 2**
Bed sheets	480	1033	480	1033
Uniforms	0	120	0	120
Pencil cases	1440	1520	1440	1520
Bags	385	240	386	239
Jackets	760	840	760	840
Camibusos	360	480	360	480
Vests	480	1033	480	1033
Pants	288	0	288	0

Table 4. Allocation Two Clusters.

	Mathematical model			**Heuristic allocation**		
Productos	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 1**	**Cluster 2**	**Cluster 3**
Bed sheets	480	0	1033	479	0	1034
Uniforms	120	0	0	120	0	0
Pencil cases	1520	1440	0	1520	1440	0
Bags	240	180	205	239	179	207
Jackets	480	360	760	480	360	760
Camibusos	0	360	480	0	360	480
Vests	553	480	480	553	479	481
Pants	0	288	0	0	288	0

Table 5. Allocation Three Clusters.

	Mathematical model				**Heuristic allocation**			
Productos	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**
Bed sheets	0	0	1033	480	0	0	1034	479
Uniforms	0	120	0	0	0	120	0	0
Pencil cases	0	720	800	1440	0	720	800	1440
Bags	205	240	0	180	205	241	0	179
Jackets	360	480	360	400	360	480	360	400
Camibusos	360	0	480	0	360	0	480	0
Vests	0	553	480	480	0	555	479	479
Pants	288	0	0	0	288	0	0	0

Table 6. Allocation Four Clusters.

The comparisons between the mathematical model and the allocation results from the heuristic are mostly similar in the three cases, implying that the approach used for the algorithm is efficient and reaches almost the optimal solution of the mathematical model for the order allocation among the clusters.

4.5. Case study and simulated scenarios

The case study is focused on informal sewing workshops located in Usme, a low-income area of Bogota, Colombia. These microbusinesses are currently working with the social program of the Engineering Faculty at the Pontificia Universidad Javeriana Bogota (PROSOFI). The sewing workshops produce bed sheets, uniforms, pencil cases, bags, vests, jackets, camibusos and pants. These products are sold to satellite warehouses, by make to order and in their own shops.

Through these case study, were generated scenarios characterized by 9 microbusinesses, 8 products and 7 types of machines, overall 63 machines. The information needed about the microbusinesses, their location, the products that this enterprises manufacture, the machines they have and all the production parameters as for example, processing times, was collected through surveys (Appendix 2 – Sheet D). The generated scenarios, as benchmarks for the problem, are based on the production order and the willingness of the microbusinesses to manufacture other products different from the ones currently produced by them (willingness other products). The values selected are explained down below.

Production order: Xiang, Song and Ye (2012) described that an industrial cluster usually has three possible statuses related with the production load (which can be in low load, in high load or in disequilibrium), so there were built these possibilities and were added two more: the equilibrium load, as the reference one, and a medium load.

Equilibrium load: Is the base scenario. The quantity of units corresponds to the production load which the association is available to complete more or less in the planning horizon (15 days, 8 hours per day). The units per product were decided according to the capacity of the association for each product.

Low load: The quantity of units per product is a quarter of the production load considered in the equilibrium level.

Medium load: The quantity of units per product is a half of the production load considered in the equilibrium level.

High load: The quantity of units per product is one and a half the quantity of the production load considered in the equilibrium level.

Disequilibrium load: The quantity of units per product is a random number between the quantity considered in the low level and in the high level.

Scenarios	Bed sheets	Uniforms	Pencil cases	Bags	Jackets	Camibusos	Vests	Pants
Low load	114	9	223	47	121	64	114	22
Medium load	228	18	446	94	241	127	228	44
High load	684	54	1338	282	723	380	684	131
Disequilibrium load	238	24	598	244	417	361	446	82
Equilibrium load	456	36	892	188	482	253	456	87

Table 7. Scenarios.

Willingness other products: Aiming to generate different scenarios, there were randomly built three different possibilities for this parameter:

Medium level: Microbusinesses are willing to participate in another product with probability 0,5

Total level: Microbusinesses are willing to participate in another product with probability 1

Low level: Microbusinesses are willing to participate in another product with probability 0,25

Next, the scenarios are constructed combining the previous loads for production orders and levels for willingness to manufacture other products. The indicators per scenario are presented in the following section of results.

5. Results

5.1 Indicators

- **Gini index**

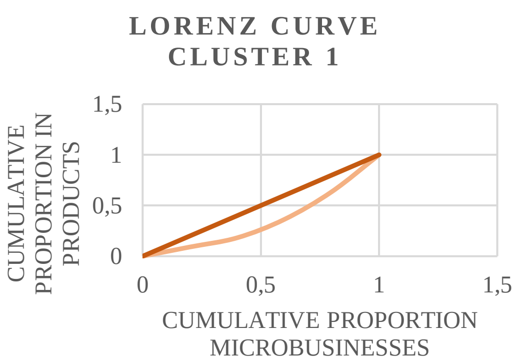
The Gini index is calculated as a measure of performance for the clusters generated in the association stage (Appendix 10 – Sheets A to H). The index is calculated for two criteria: products and machines, and represents the inequality expected inside the clusters as a signal of integral clusters. The resultant coefficients range from 0 to 1, with 0 representing perfect equality and 1 representing perfect inequality. According to this, coefficients far from 0 are preferred and reveal diversity of microbusinesses in each cluster.

The Gini Index corresponds to the following formula:

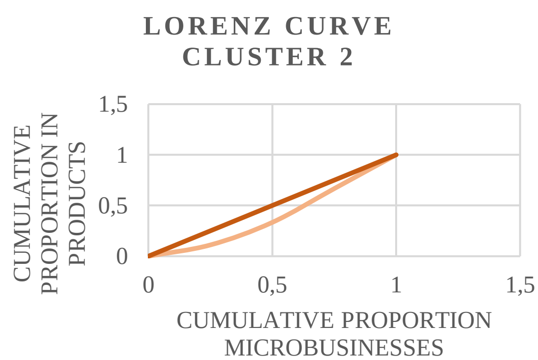
$$Gini\ Index = 1 - 2Z \quad (Equation\ 3)$$

Z corresponds to the area under the Lorenz curve. This curve illustrates the relation between the proportion of the microbusinesses and the cumulative proportion of products manufactured by each microbusiness belonging to the cluster.

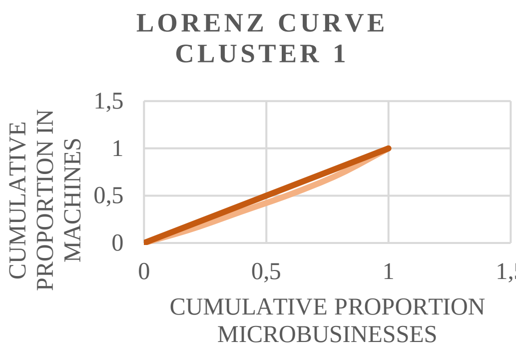
The results of the solution with two clusters and for the criterion products are displayed in the Graphics 3 and 4, in which each cluster has its respective Lorenz curve. Likewise, the same results for the criterion machines are displayed in the Graphics 5 and 6.



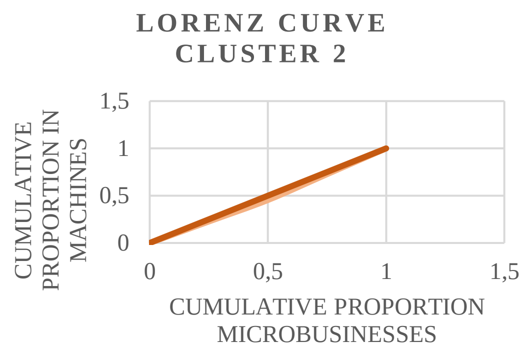
Graphic 3. Lorenz curve for products. The Gini Index corresponds to 0,29.



Graphic 4. Lorenz curve for products. The Gini Index corresponds to 0,19.



Graphic 5. Lorenz curve for machines. The Gini Index corresponds to 0,10.



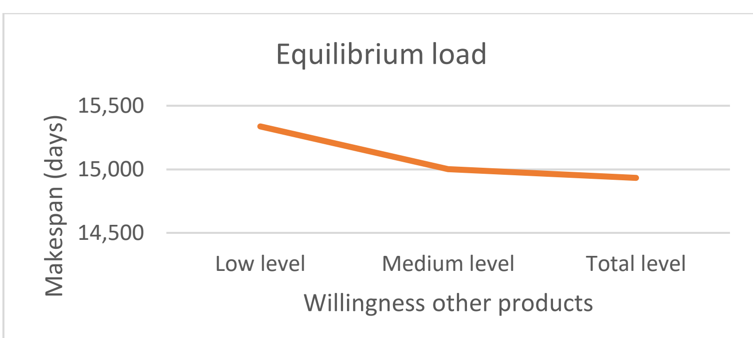
Graphic 6. Lorenz curve for machines. The Gini Index corresponds to 0,04.

The Lorenz curve is compared with the 45-degree line, which represents perfect equality, in this case is preferred to be far from this line, in which the Gini index will be bigger, hence the graphics 3,4 and 5 show good clusters. The Gini Index in most cases varies among 0,19 for the criterion products and 0,07 for the criterion machines, this denotes an acceptable level of inequality inside the clusters.

- **Makespan**

The results obtained per scenario for the indicator makespan are presented in the Appendix 10 – Sheet I. Analyzing a particular scenario, each cluster complete the products in a day that is called the makespan per cluster. The makespan of the association is the maximum makespan of the clusters.

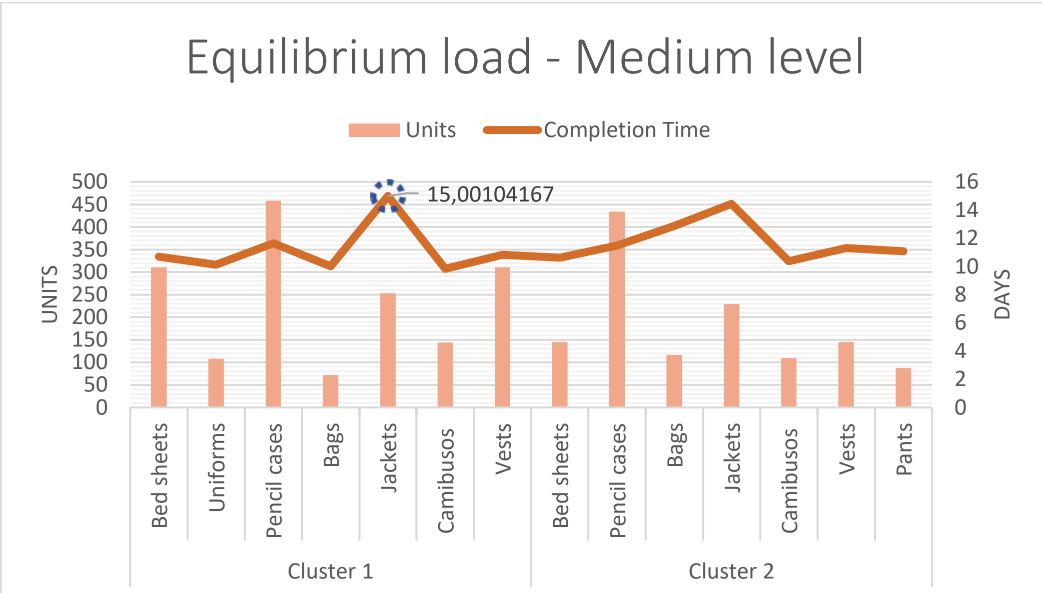
The Graphic 7 summaraizes the results of the scenarios with equilibrium load. The graphic is useful to demonstrate the behavior of the makespan of the scenarios with this production order load, but with different levels of willingness to manufacture other products. It is found that if the willingness to manufacture other products is low, then the makespan is higher. In the other side, if the willingness to manufacture other products is medium or total, then the association reaches better completion times so the makespan is lower. For the graphics of the other scenarios also view the Appendix 10 – Sheet I.



Graphic 7. Makespan of the scenarios with equilibrium load.

- **Completion time for products and orders**

The Graphic 8 shows the results of the completion time for each product per cluster and the corresponding units made at that date. The case displayed is the equilibrium load and the total level willingness, it is visible that the units between clusters for each product are closely distributed and maintain roughly equity. The results for the other scenarios are in the Appendix 10 – Sheets J to X.



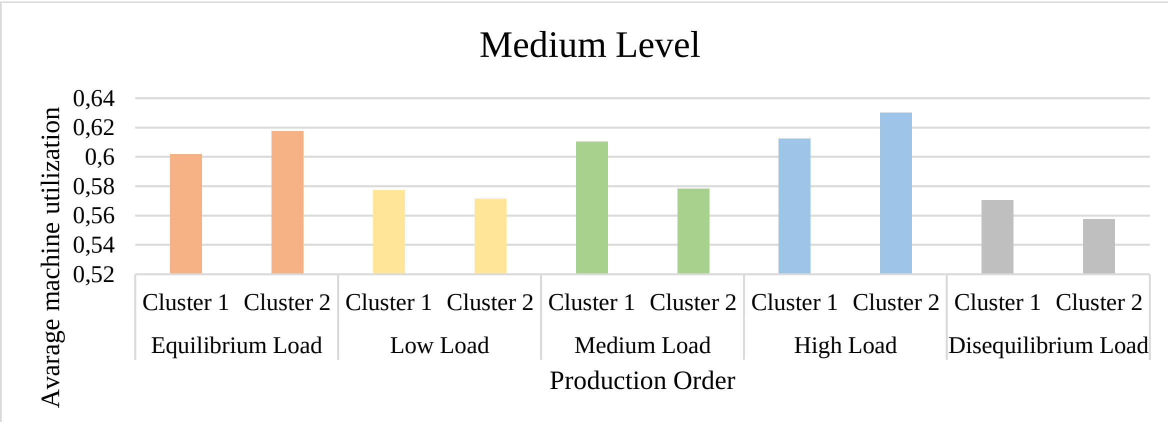
Graphic 8. Completion time equilibrium load-total level.

The completion time across the clusters and products varies around 11 days for the equilibrium load, for the disequilibrium load is almost the same time, for the high load is on average 17 days, for the low load usually less than 4 days and for the medium load is approximately 6 days overall.

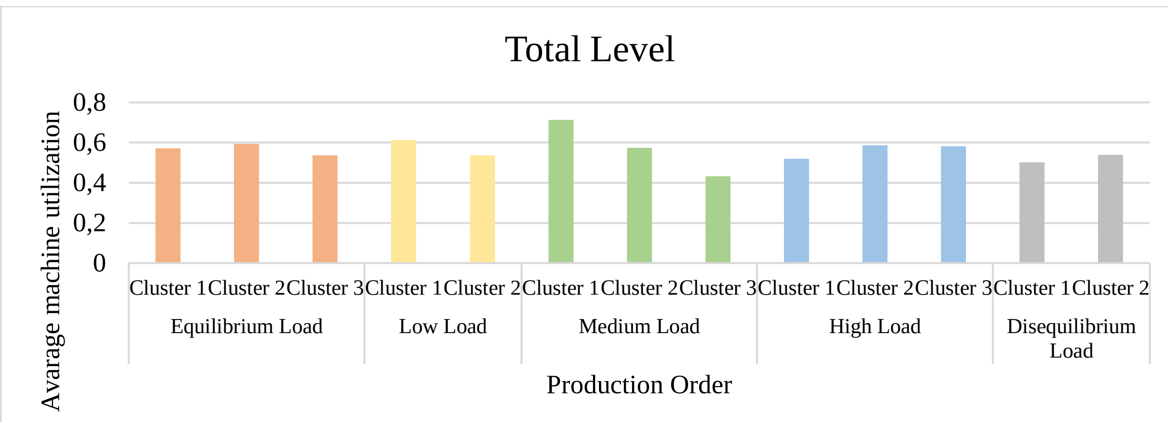
Across the willingness to produce certain products the completion time is extremely variable; hence the impact of these levels relies upon the production order and the initial capacity to produce each product.

- **Utilization level**

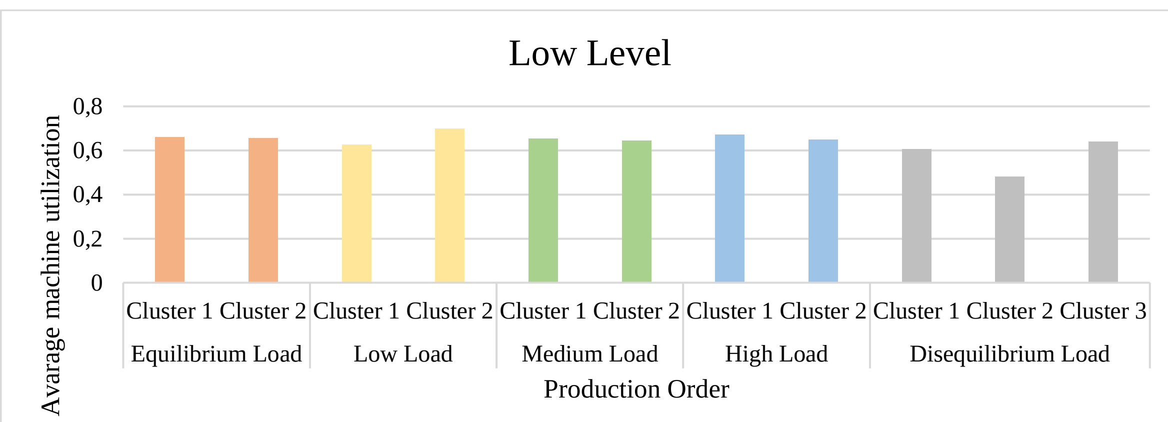
The percentage of use of the machines (utilization level) in all the scenarios tested are presented in the Appendix 10 – Sheets Y to AN. The corresponding graphics are shown below, and reflect for each level of willingness to manufacture other products, the behavior of the utilization level per cluster with different production loads.



Graphic 9. Utilization level with medium willingness to manufacture other products.



Graphic 10. Utilization level with total willingness to manufacture other products.



Graphic 11. Utilization level with low willingness to manufacture other products.

Analyzing the previous graphics, it can be observed that no machine is empty or unused and most of them have an average of utilization percentages higher than fifty percent (50%).

5.2 Statistical analysis

In order to test the statistical significance of the production load and the willingness other products effect over the makespan, a factorial design is conducted. The experimental design corresponds to a Production load (4) x Willingness other products (3) factorial design, where the numbers in parentheses indicate the number of levels. The analysis is made through an ANOVA (table 8) and its interpretation is obtained based on main effect plots and interaction plots.

	Sum of Squares	Degrees of freedom	Mean Square	F Ratio	P Value
Production load	350990533.4	3	116996844.5	6236.1	7.9E-35
Willingness other products	8404362.5	2	4202181.3	224.0	3.0E-16
Interaction	20153313.1	6	3358885.5	179.0	1.0E-18
Error	450269.9	24	18761.2		
Total	379998478.9	35	10857099.4		

Table 8. ANOVA for Production load and Willingness other products

According to the previous results the main effects of the factors are statistically significant at the traditional significance levels, additionally the interaction effects are also significant. The plots in Appendix 10 – Sheet AO show that the level in which each factor minimizes the makespan, is low production load and total willingness to manufacture other products. Nevertheless, the interaction effect shows that the medium level for willingness combined with low production order also reaches the minimum objective function.

6. Conclusion

- The heuristic proposed above reaches satisfactory clusters and production allocations, near the optimums obtained in the mathematical models.
- The performance measures show equity among the utilization level of the machines, confirming the harnessing of the machines. Moreover, the distribution of the production orders is reasonable among the clusters as well as inside the clusters.
- The results of the factorial design indicate that the low production load combined with medium and/or total willingness to manufacture other products are the best levels for the factors in order to achieve the minimum makespan in the allocation solution.
- Through the generated scenarios of the case study and the statistical analysis, was found that the willingness of the microbusinesses to manufacture other products different from the ones currently produced by them has a positive impact over the makespan of the cluster. Therefore, it is evidenced and quantified the effect of the cooperation and the sharing of knowledge mentioned by other authors to reach a successful association.

7. Recommendations

- The association stage includes until the conformation but does not include ways to negotiate or cooperate among them. In order to implement the solution in coordination with the microbusinesses is imperative to pre-define the design and the road map of each product.

8. Future work

- It is important to state that the method provides a solution for the context of textile microbusinesses. Nevertheless, future works could reply the method to other businesses and other sectors.

- The method allows the addition of new criteria, as product quality, know-how of the workers and inventory capacity. This implies the repetition of the AHP technique for the new set of criteria.
- It is suggested that before processing times are introduced to the method, a line balancing analysis should be carried out in order to relax the assumption that there is a worker per workstation.
- The incorporation of stochastic processing times, transportation times and time spent in the acquisition of inputs, may lead to better approximations towards the real dynamics of the microbusinesses.
- A future improvement of the method might involve priorities for products and microbusinesses for the allocation stage.
- A natural progression of this work is to analyze circumstances in which a microbusiness not only receives production orders from the association but also its own production orders.
- Considerably more work will need to be done to determine the geographical distances only by having the address of the microbusinesses, this involves the integration of Google APIs.
- Lot-sizing constitutes a separate problem related to the scheduling; this would be a fruitful area for further work.

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