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A multi-objective meta-heuristic approach for the design and planning of green supply chains - *MBSA*

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ABSTRACT

Supply Chains are complex networks that demand for decision supporting tools that can help the involved decision making process. Following this need the present paper studies the supply chain design and planning problem and proposes an optimization model to support the associated decisions. The proposed model is a Mixed Integer Linear Multi-objective Programming model, which is solved through a Simulated Annealing based multi-objective meta-heuristics algorithm – MBSA. The proposed algorithm defines the location and capacities of the supply chain entities (factories, warehouses and distribution centers) chooses the technologies to be installed in each production facility and defines the inventory profiles and material flows during the planning time horizon. Profit maximization and environmental impacts minimization are considered. The algorithm, MBSA, explores the feasible solution space using a new Local Search strategy with a Multi-Start mechanism. The performance of the proposed methodology is compared with an exact approach supported by a Pareto Frontier and as main conclusions it can be stated that the proposed algorithm proves to be very efficient when solving this type of complex problems. Several Key Performance Indicators are developed to validate the algorithm robustiveness and, in addition, the proposed approach is validated through the solution of several instances.

1. Introduction

Traditionally the design and planning of supply chain networks (SCN) has been undertaken based on individual concepts and applying only economic objectives, such as cost minimization or profit maximization. However, the increasing market competition, the customers' change expectations, on the value of goods and services, combined with advances in technology and fast access to information demanded for an integrated view when managing supply-chain (SC) networks (Papageorgiou, 2009). In addition, the worldwide extension of business led to the availability of sets of alternative resources, as well as to a vast array of potential customers, justifying the current need of efficient SC management. Simultaneously, society has been developing an increasing level of awareness for environmental sustainability and companies have been realizing that economic objectives ought no longer to be the single concern of supply chains as environmental impacts resulting not only from their structures, but also from their operation need to be minimized (Seuring, 2013; Mota, Gomes, Carvalho, & Barbosa-Povoa, 2015). Dekker, Bloemhof, and Mallidis (2012) state that "Improving environmental quality comes at a cost, so the question is which trade-offs occur between the environmental impacts of an economic activity and its costs, and what are the best solutions for balancing ecological and economic concerns?". This raises the concept of building eco-efficient solutions. Thus it becomes necessary to define an efficient integration of these SC main aspects when planning and designing SC so as to minimize environmental impacts while maximizing profit and responsiveness.

Some research has already been done towards this identified goal, where the most used methodologies have been based on exact approaches, as MILP and MINLP (Papageorgiou, 2009), but focusing in single objectives. The inclusion of several objectives requires a multi-objective approach, which adds to the already high computational burden characterizing SC problems resolution (Papageorgiou, 2009; Barbosa-Póvoa, 2014). Thus new solutions approaches are to be explored to overcome this drawback. Some of them may be problem oriented, such as heuristics, evolutionary algorithms, meta-heuristics, hybrid methods or even math-heuristics.

This paper follows this need and aims to contribute to fulfill this gap by proposing a *multi-objective, multi-start, meta-heuristics algorithm,* MBSA, for the design and planning of supply chains (SC) where

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both economic and environmental objectives are taken into account. At the strategic level the algorithm provides the location and capacities of facilities, warehouse and distributions centers and selects the best multipurpose technology to be allocated to each facility. To cope with realistic problems multiproduct characteristics are considered, triggering flexible and multipurpose facilities. At the tactical level, the algorithm, defines the production planning, material flows, inventory profiles and distribution strategies allowing for X-docking. Moreover, the environmental aspects are integrated at the design level by using an end-point indicator, where all the emissions associated to products productions and distribution are quantified. The multi-objective approach where profit maximization and environmental impacts minimization are considered simultaneously uses small amounts of computation time. This appears as quite innovative having in mind the complexity of the problem in study. Such performance is based on the use of an efficient multi-start local search algorithm that trough a Simulating Annealing meta-heuristic is able to search the entire objective space. The quality, robustness and variability of the algorithm solution are analyzed through a sensitive analysis followed by a comparison with the exact approach.

As main result the proposed approach presents to the decision-maker a set of non-dominated solutions that define the Pareto frontier, where for each solution the strategic and tactical aspects are characterized.

This remain of this paper is organized as follows; in Section 2 a literature review is presented, followed by the problem description in Section 3. Section 4 characterizes in detail the solution approaches developed and in Section 5 Key Performance Indicators (KPI) are proposed and explored in detail. The instance characterization is shown in the Section 6, followed by algorithm results analysis and discussion in Section 7. To finalize Section 8 presents the conclusion and some final remarks on future work.

2. Literature review

Supply Chain optimization is nowadays an important and thriving research area of modern enterprises as their supply chains are becoming more and more complex systems demanding for supporting tools to inform the involved decision making processes (Grossmann, 2012). From strategic to operational decision levels this need has been clearly identified by academics and industrials (Papageorgiou, 2009). The most common developed approaches to tackle this problems are based on exact formulations (e.g. Cardoso, Barbosa-Povoa, & Relvas, 2013; Pasandideh, Niaki, & Asadi 2015; Salema, I., Barbosa-Povoa, & Novais, 2010), which when applied to real case problems often present solution difficulties associated with large computational times. Thus the development of alternative solutions methodologies that prove efficient is still a challenge research area where much has still to be done (Melo, Nickel, & Saldanha-da-Gama, 2009; Barbosa-Póvoa 2014). Recently some authors have been trying to address this problem using methodologies that embed the problem characteristics resulting in heuristics algorithms.

In, Wang, Makond, and Liu (2011) addressed a location–allocation problem through a bi-level stochastic formulation of a two-echelon supply chain considering uncertainty in the demand. The authors developed a genetic algorithm with greedy heuristics and the results reveal that the algorithm can efficiently yield nearly optimal solutions against stochastic demands. Later on, Kadadevaramath, Chen, Shankar, and Rameshkumar (2012) explored several variations of particle swarm algorithms for solving a constrained multi echelon supply chain network considering the minimization of the total supply chain operating cost. One year later, Shankar, Basavarajappa, Chen, and Kadadevaramath (2013) developed a multi-objective hybrid particle swarm algorithm that considered simultaneously the costs minimization, defined by facilities location and shipment costs, and the maximization of the customer demands. The problem involves a single-product, four-echelon supply chain architecture. Zhang, Li, Qian, and Cai (2014) also explored the supply chain network design problem with the aim of defining the locations of the distribution centers and the assignment of customers and suppliers to the corresponding distribution centers. The formulation explored a Lagrangian relaxation based algorithm and the results were compared with the exact approach CPLEX showing that the proposed algorithm presented a stable performance and outperformed CPLEX for large-scale problems. Recently, Ren et al. (2015) developed a mixed-integer non-linear model with the aim of helping the decision-maker to select the most sustainable design and planning supply chain network. The SC structure considers multiple feed stocks, transport modes, regions for production and distribution centers. A sustainable measure was explored, which was based on the energy sustainability index trough a life cycle perspective. Fung, Singh, and Zinder (2015) developed a procedure with the aims of infrastructure expansion minimization cost to face future demand variability in a mineral supply chain. A matheuristic formulation was designed based on the hybridization of mixed integer linear programming (MILP) and a simulated annealing approach taking advantages of different levels of data aggregation. The procedure demonstrated the ability to solve industrial problems of different sizes. Camacho-Vallejo, Munoz-Sanchez, and Luis Gonzalez-Velarde (2015) considered in its work the production planning and distribution of a supply chain with the aim of operation and transport costs minimization in a four echelon supply chain. A heuristic algorithm based on Scatter Search that considers the Stackelberg's equilibrium was developed for the problem solution. The algorithm developed shown better results than the existing best known results in the literature,

The above works show the increasing investment on alternative solution techniques to support the development of expert systems able to solve real supply chains problems. Such works presented promising solution approaches but are still away from providing solution techniques that account for multi-objective SC problems where simultaneously with the SC modeling complexity both economic and environmental objectives are considered. Within this context the main contributions of the present work are twofold. On one hand, from a formulation viewpoint the SC decision complexity is modeled where simultaneously the design and planning problems are considered allowing for the location and sizing of different entities and associated technologies, while pursuing trade-offs between economic and environmental objectives. On the other hand and from an algorithm solution viewpoint an efficient solution approach is developed, which, from the best of our knowledge, explores for the first time a multi-objective approach using a multi-start strategy, to characterize and define the Pareto frontier solution.

3. Problem description

The work by Pinto-Varela, Barbosa-Povoa, and Novais (2011) presented a generic formulation for the design and planning of SCs, while considering simultaneously economic and environmental aspects. The supply chain network is characterized by n-echelons, where first and second level suppliers, manufacturers, wholesalers, retailers and markets are present. It includes a set of manufacturing facilities that employ a set of resources technologies that are multipurpose in nature (i.e. more than one product can be produced sharing the available resources). From a strategic point view, the network comprises several entities, namely production facilities, warehouses (WH) and distribution centers (DC) selected from a set of potential locations where the former employ the selected so-called resource technologies (i.e. production lines, storage resources, connections, etc.). At a tactical level the supply chain defines the capacities, the planning of each resource usage, as well as the materials flows within the

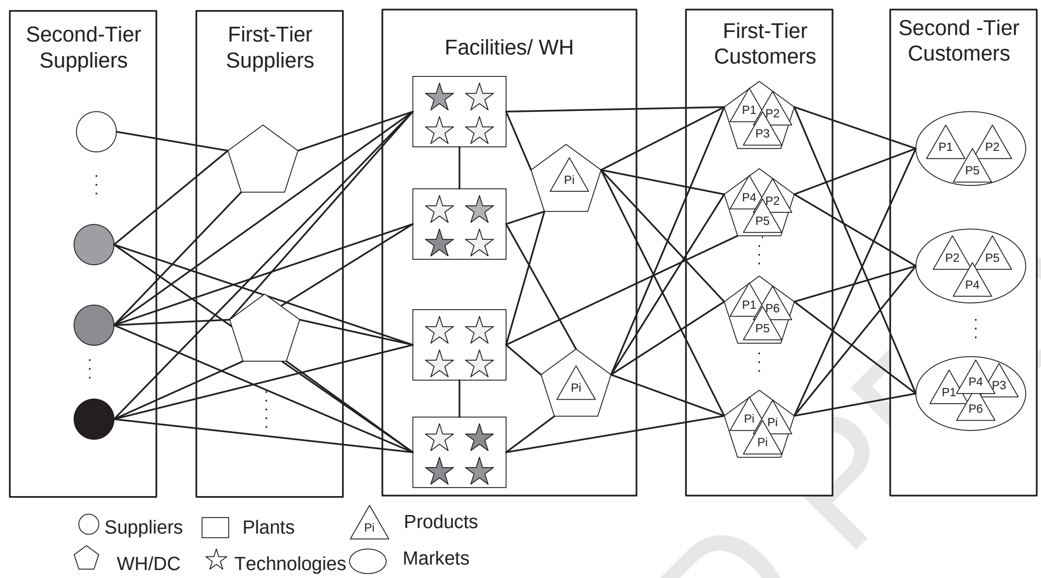

Fig. 1. Schematic representation of the SCN.

network are defined. Production levels, material storage handling, and resources' capacities are limited within certain bounds, while the final products amounts to be sold in each market are to be satisfied. Storage at the warehouses and distribution centers can be either multipurpose or dedicated and just-in-time procedures or finite capacity storage may also co-exist with X-docking. In economic terms, the cost of facilities installation, as well as operational, storage, transportation and raw materials costs are considered simultaneously with products' revenues. In environmental terms the impacts generated by electricity and diesel consumption over the entire SC are accounted for. Fig. 1 depicts the structure considered and its characteristics.

4. Solution approach

The previous problem representation will be implemented and explained through the characterization of one illustrative instance and applying a novel bi-objective meta-heuristic algorithm. The results obtained are compared with those of a bi-objective exact approach obtained through the ε-constraint as presented by Pinto-Varela et al. (2011). The problem formulation involves the following sets parameters, variables, objectives functions and constraints:

Sets:
- d set of damages
- f set of facilities
- k set of processes(tasks) embedded in a resource technology
- p set of pollutants emitted
- r set of all resources, both renewable and non-renewable
- u set of utilities

Parameters:
- CC_r^i fixe/variable installation cost
- CCF capital charge factor
- F_f maximum amount of resource technologies available in facility f
- H planning horizon per year
- HourYr number of hours per year
- $NormF_g$ weighted value of damage g
- Q_r^{min}, Q_r^{max} min, max capacity available for resource r
- R_r^{min},R_r^{max} minimum, maximum demand of the resource at H
- v_r,P_r resource price, raw material and product, respectively
- α_k^0,α_k^1 fixed and variable cost coefficients for technological processes
- α_{uk}^F,β_{uk}^F fixed and variable utility cost coefficients for the technological process
- α_{ur}^{WD}, β_{ur}^{WD} fixed and variable utility cost coefficients for dedicated warehouse and distribution center
- $\mu_{kr\theta}$, $\nu_{kr\theta}$ renewable or non-renewable resource utilization
- ϕ_r^{max}, ϕ_r^{min} resource technology size factor
- $\Omega_{u,p}$ quantity of pollutant emitted to generate an unit of consumed utility u
- η_u amount of diesel consumed m^3/km
- ς_{dp} impact factor coefficient
- λ_{pr}, λ_{pf}, λ_{pu} defines the quantity of pollutants p, emitted per unit mass of resource r used, soil occupation and utility consumed, respectively

Decision variables:
- P_{rt} amount of material delivered from the resource technology r in instant t
- Q_r capacity of resource technology r
- R_{rt} excess of resource at t
- UT_u total amount of utility consumed
- ξ_{kt} production, storage size of technological process k at time t
- N_{kt} technological process selection k at instant t
- $y_r = -1$ if resource technology r is used; 0 otherwise
- $y^f = 1$ if the facility is opened; 0 otherwise

Environmental variables:
- Dam_d^{SC} set of damages
- $Eco99$ environmental indicator
- Q_p^{Utotal} total amount of pollutants emitted

Bi-objective model: *max Profit, min Eco*99

$$Eco\,99 = \sum_d NormF_d Dam_d^{SC} \tag{1}$$

$$Profit = \left[\sum (R_{rt}+P_{rt})p_r - \left(\begin{array}{c} \sum_{r\in C_f}(R_{ro}-R_{rt})\nu_r + \sum_t \sum_{k\in T_P}\left(\alpha_k^0 N_{kt} + \alpha_k^1 \xi_{kt}\right) + \sum_{r\in C_r/C_f} R_{rt} CC_r^s \\ + \sum_{r\in W_C}\left(y_r CC_r^0 Km_r + Q_r CC_r^1\right) \end{array} \right) \\ - \sum \nu_u \left[\eta_u \sum Km_r y_r^c + UT_u \right] \right] \times \frac{HourYr}{H} \\ - \left(\sum_{r\in Wp}\left(y_r CC_r^0 + Q_r CC_r^1\right) + \sum_{r\in W_\nu}\left(y_r CC_r^0 + Q_r CC_r^1\right) \right) \times CCF \tag{2}$$

Subjecto to:

$$R_{rt} = R_{r_0|t=1} + R_{r,t-1|t\geq 2} + \sum_k \sum_{\theta=0}^{\tau_k} \left(\mu_{kr\theta} N_{k,t-\theta} + \upsilon_{kr\theta}\xi_{k,t-\theta}\right) + P_{rt} \tag{3}$$

$$\forall r \in W_p t = 1, \ldots, H+1$$

$$\times \sum_{t'=t-\tau_k+1}^{H} \sum_{k\in T_r} N_{kt'} \leq y_r \quad \forall \mathrm{r} \in \mathrm{W_p} \tag{4}$$

$$\phi_{kr}^{\min} Q_r N_{kt} \leq \xi_{kt} \leq \phi_{kr}^{\max} Q_r N_{kt} \quad \forall \mathrm{k} \in \mathrm{T_p}, \mathrm{r} \in \mathrm{C}, \mathrm{t} = 1, \ldots, \mathrm{H} \tag{5}$$

$$N_{kt} = \sum_{j=1}^{N_k^{\max}} j \tilde{N}_{jkt} \quad \forall \mathrm{k} \in \mathrm{T_p}, \mathrm{t} = 1, \ldots, \mathrm{H} \tag{6}$$

$$\sum_{j=0}^{N_k^{\max}} \tilde{N}_{jkt} \leq 1 \quad \forall \mathrm{k} \in \mathrm{T_p}, \mathrm{t} = 1, \ldots, \mathrm{H} \tag{7}$$

$$Q_r^{\min} \tilde{N}_{jkt} \leq \underset{rjkt}{\tilde{Q}} \leq Q_r^{\max} \tilde{N}_{jkt}$$
$$\forall k \in T_p, r \in W_p, j = 1, \ldots, N_k^{max}, t = 1, \ldots, H \tag{8}$$

$$\sum_{j=0}^{N_k^{\max}} \tilde{Q}_{rjkt} = Q_r \quad \forall k \in T_p, r \in W_p, t = 1, \ldots, H \tag{9}$$

$$\phi_{kr}^{\min} \sum_{j=1}^{N_k^{\max}} j \tilde{Q}_{rjkt} \leq \xi_{kt} \leq \phi_{kr}^{\max} \sum_{j=1}^{N_k^{\max}} j \tilde{Q}_{rjkt}$$
$$\forall k \in T_p, r \in W_p, t = 1, \ldots, H \tag{10}$$

$$Q_r^{\min} y_r \leq Q_r \leq Q_r^{\max} y_r \quad \forall r \in W_p \tag{11}$$

$$R_{rt} \leq \phi_r^{\max} Q_r \quad \forall r \in W_\nu, k \in T_V, t = 1, \ldots, H+1 \tag{12}$$

$$Q_r^{\min} y_r \leq Q_r \leq Q_r^{\max} y_r \quad \forall r \in W_\nu \tag{13}$$

$$\sum_{r\in C_f} \left[R_{r_0} - R_{rt} \right] \leq Q_{r|r\in W_{rm}} \quad t = 1, \ldots, H+1 \tag{14}$$

$$\sum_{r\in C_p} R_{rt} \leq Q_{r|r\in W_{fp}} \quad t = 1, \ldots, H+1 \tag{15}$$

$$\xi_{kt} \leq \phi_{kr}^{\max} Q_r \quad \forall k \in T_T, r \in W_c \tag{16}$$

$$Q_r^{\min} y_r \leq Q_r \leq Q_r^{\max} y_r \quad \forall r \in W_c \tag{17}$$

$$R_r^{\min} \leq R_{rt} \leq R_r^{\max} \quad \forall r \in C_p, \ t = 1, \ldots, H+1 \tag{18}$$

$$y^f \geq \sum_{r\in T_r^f} y_r \quad \forall f \in F \tag{19}$$

$$UT_u = \sum_t \sum_{k\in T_p} \sum_{\theta}^{\tau_k} \left(\alpha_{uk}^F N_{kt-\theta} + \beta_{uk}^F \xi_{kt-\theta} \right)$$
$$+ \sum_{r\in W_\nu} \alpha_{ur}^{WD} y_r + \sum_t \sum_{r\in W_\nu} \beta_{ur}^{WD} R_{rt} \tag{20}$$

$$Q_p^{Utotal} = \sum_u \Omega_{u\,p|p\in E} \left(UT_u + \eta_u \sum_{r\in W_c} Km_r y_r \right) + \sum_f \lambda_{pf|p\in L} y^f$$
$$+ \sum_{r\in C_f} \lambda_{pr|p\in N} \left(R_{r_0} - R_{rt|t=1+H} \right) + \sum_u \lambda_{pu|p\in N} UT_u \tag{21}$$

$$Dam_d^{SC} = \sum_p \varsigma_{dp} Q_p^{Utotal} \quad \forall d \in D \tag{22}$$

In this model, the first objective Function (1) minimizes the sum of all environmental impacts from diesel and electricity consumption along the SC. The second objective Function (2) expresses the SC network profit. The resource balances for every resource is performed by Constraint (3). Constraint (4) guarantees the technologies' multipurpose operation. The nonlinear Constraint (5), which characterizes the amount of material being processed through each technological process, is replaced by linear Constraint (10) and auxiliary Constraints (6) until (9). The resource technology capacity and design is defined through Constraint (11). The capacity and design constraints of warehouses (WH) and distribution centers are guaranteed by Constraints (12) to (15). Constraints (16) and (17) define the transportation constraints. The market demand is defined by Constraint (18), while the choice of a certain facility is defined by the choice of any of the technological resources associated to it, Constraints (19). The remaining Constraints, (20)–(22), defined utilities consumption, pollutants inventory, and environmental impact quantification, respectively.

4.1. Bi-objective exact approach

The mathematical formulation for the ε-constraint method can be summarized as follows:

$$\begin{array}{ll} Maximize\ f_u(x) & \\ s.t. & f_m(x) \leq \varepsilon_m \quad m = 1, 2, \ldots, M\, and\, m \neq u \\ & g_j(x) \leq 0 \quad j = 1, 2, \ldots; \\ & h_k(x) = 0 \quad k = 1, 2, \ldots, K; \\ & x_i^{(L)} \leq x_i \leq x_i^{(U)} \end{array} \tag{23}$$

where ε_m represents an upper bound of the value of f_m. This technique entails handling one of the objectives and restricting the others within user-specified values. Firstly the upper and lower bounds are determined by the maximization of the profit and minimization of the Eco99. The optimization problem (maximization) is implemented with the objective function being the profit and the Eco99 as a constraint, varying between its lower and upper bounds. As result the efficient frontier is obtained, which allows the decision maker to select any solution depending on the relative worthiness of each objective.

4.2. Bi-objective meta-heuristic approach

The model presented when applied to large problems often results in high time consuming. In order to overcome this issue, a meta-heuristic approach is here developed. This is based on the Simulated Annealing (SA) algorithm proposed by Kirkpatrick, Gelatt, and Vecchi (1983) and Černy et al. (1985), where several adaptations were developed so as to improve the algorithm's efficient and effective application to the SCN characteristics.

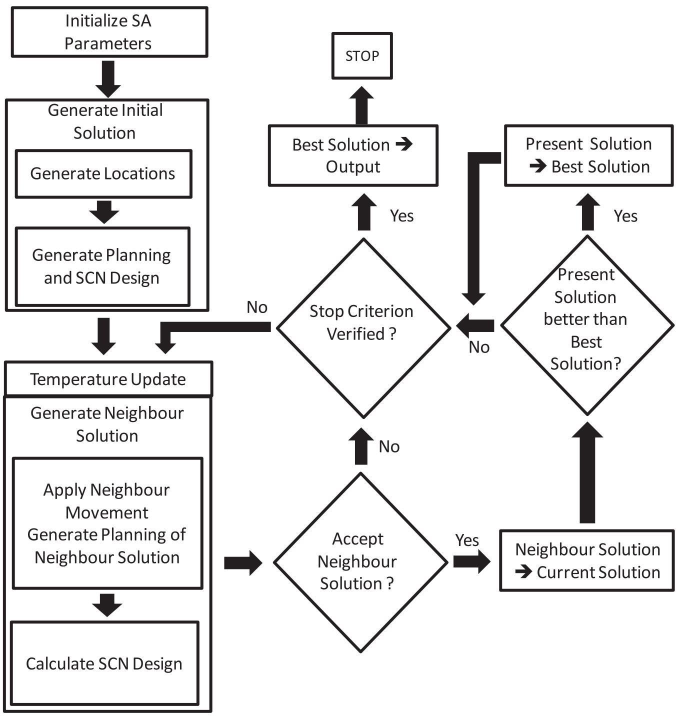

Fig. 2. Classic Simulation Annealing algorithm.

SA can be classified as a Local Search Meta-Heuristic, which requires not only an initialization procedure that can be done by a randomly feasible solution or with a constructive heuristic. A classic SA characterization is shown in Fig. 2. A random initialization procedure is used by the algorithm, where the initial random feasible solution is improved iteratively and another solution from the neighborhood of the current one is chosen. In order to prevent an early stop of the algorithm on a local optimum and to guarantee efficiency and effectiveness, a mechanism based on the Metropolis Algorithm is incorporated.

To overcome the mono-objective classic SA approach, this work goes one step forward and, a SA bi-objective approach is developed. An approximation of the Pareto frontier (PF) is explored, as exhaustive as possible, using as objective functions the profit maximization and environmental impact minimization. The efficient SC designs solutions are characterized in the Pareto Frontier and, for each SC topology a reasonable number of efficient solutions should be included. This information becomes more relevant in situations where a tight budget exists and the decision maker will need a decision support tool to help him/her on the selection of the most adequate compromise solution based on the knowledge of those efficient solutions' characteristics (similar cost and within the available budget). These results became more relevant as the problem complexity increases and the exact approaches face computational difficulties to explore the efficient region. This work aims to overcome this limitation, by proposing the *MBSA* algorithm.

4.2.1. MBSA algorithm characterization

The new algorithm characterization, defined as MBSA algorithm is shown in Fig. 3. The main procedures are highlighted and will be addressed in detail below.

MBSA involves five different procedures. The first procedure (I) is related with the generation of the initial solution of each algorithm restart. The second (II) one defines the neighbor solution generation. The third procedure (III) analyzes the new solution acceptability. Finally the fourth and fifth procedures (IV, V), define respectively the neighbor solution efficiency, the restart mechanism and the stop criterions control.

4.2.2. First Procedure I

Procedure (I) is related with the generation of the initial solution of each algorithm restart. These solutions are obtained from a constructive heuristic, which raise several questions

1. How should solutions be codified when the Meta-Heuristic is being implemented?
2. Which facilities will be opened?
3. Which production technologies will be selected?
4. When/How much/What products in each facility will be produced?
5. How will be the product distribution performed?

After those variables are settled, the SCN design will be defined, since the available capacities will have to be sufficient to ensure that all the required production, warehousing and transportation are satisfied. Finally, the associated profit and environmental impact are quantified.

Constructive Heuristic Characterization: this procedure follows several steps which will be detailed, using the time horizon defined as H.

1. For each market, assume that all distribution centers are installed and randomly generate a final stock of each final product that verifies the demand constraints;
2. Select randomly the production facilities to be installed;
3. Set the time instant $t = H$;
4. For every production facility generate randomly the batch size being processed;
5. Calculate the flows outgoing from the facilities to the warehouses/distribution centers, at the end of each process;
6. Calculate the flows incoming to the facilities from warehouses (or other facilities, for the intermediate products) and select randomly when these flows have to occur;
7. Decrease t by one unit, $t = t - 1$;
8. If there are any incoming flows occurring at time t, correct the inventory levels, and for every intermediate product select an unoccupied facility that is going to process it and when;
9. If there is a process starting at t then for each of them generate randomly the batch size being processed. Calculate the flows incoming to the facilities from warehouses (or other facilities, for intermediate products) and select randomly when these flows have to occur;
10. Go to 7, until either $t = -1$ or the inventory levels for all intermediate and final products are null.

4.2.3. Second Procedure II

Procedure (II) of the *MBSA* is the neighbor solution generation. The neighborhood function in this case has to accommodate both objective functions, unlike the classic SA algorithms. Its characterization is detailed and a motivating example, which enhances the problem characteristics, is used to illustrate the four movements. It should be noted that the algorithm considers the Eco-Indicator symmetric values, so both functions have the same optimization direction.

The nomenclature used for the **MBSA** algorithm characterization is the following:

i – the current iteration;
s_i – the current solution;
s'_i – the randomly generated neighbor solution;
$f_1(s), f_2(s)$ – respectively, the Profit and the Eco-Indicator 99 assessed for solution s;
Pac – the probability of accepting the neighbor solution;
$T1_i, T2_i$ – the temperatures associated respectively to objective functions $f_1(s)$ and $f_2(s)$ at iteration i.

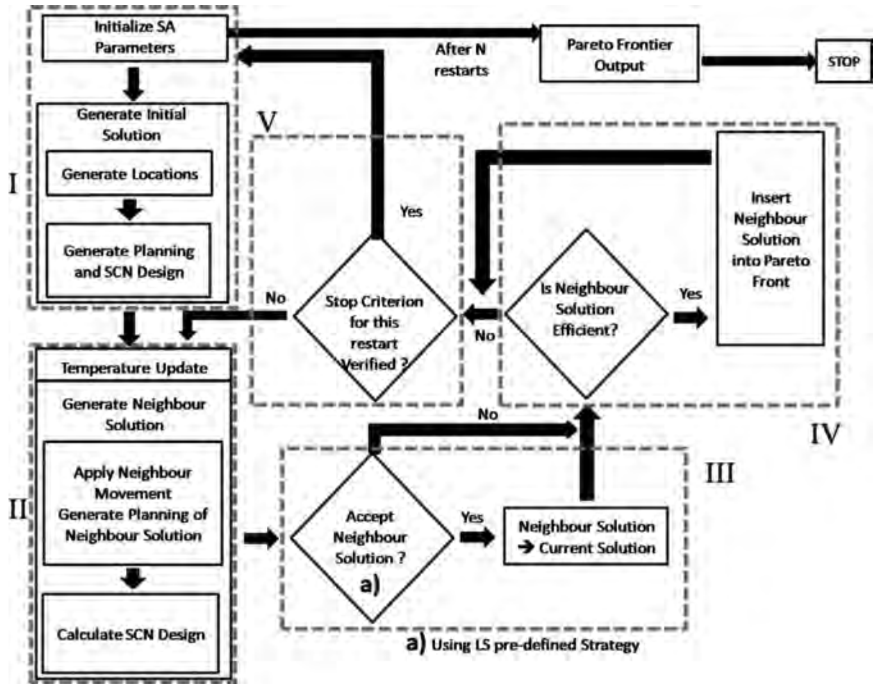

Fig. 3. Schematic representation of the MBSA algorithm.

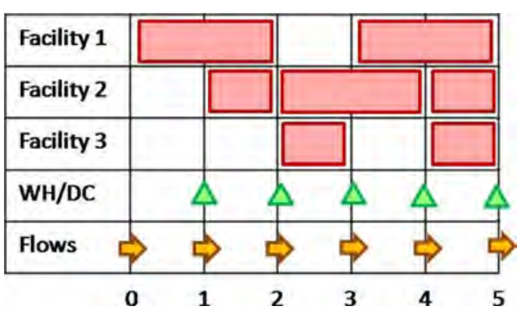

Fig. 4. Generic solution.

The temperature updating is based on a Geometric Cooling Scheduling, defined by the temperate decrease every *k*th iteration with the following expression:

1. $T_{k+1}=\alpha T_k$

where α is a constant close to *1*.

For each Objective Function the temperature T_0 is empirically adjusted in order to allow at the initial steps of the algorithm the acceptance of all neighbor solutions with a probability close to *1*. The cooling rate α was adjusted empirically to allow a slow decrease in the temperature so that the process will remain in quasi-equilibrium.

Neighbor Solution Generation: a neighbor solution is derived from the current through four possible movements

1. Quantity increase/decrease of a final product demand;
2. Delay/anticipate by 1 time unit the use of a technological process;
3. Two equivalent process may be aggregated or one single process may be slip in two equivalent ones;
4. Change facility's location.

A generic and illustrative solution is presented in Fig. 4. This involves a supply chain formed by 3 production facilities (facility 1, 2 and 3), a warehouses (WH)/distribution center (DC). The SC planning is represented by rectangles. The triangles represent the inventory levels of final and intermediate products stored in Warehouses and Distribution Centers, at the end of each time period. The arrows indicate transportation flows occurring at each instant.

When a movement is performed, it is illustrated by the corresponding rectangle's size or a shade modification and all changes on inventory levels or transportations flows will be indicated by vertical black arrows.

Movement 1. Quantity increase/decrease of a final product demand neighbor solution.

This movement procedure is detailed in Fig. 5 and illustrated on Figs. 6 and 7. In the presented example, as can be seen in Fig. 6, the final product selected on step 1.1 is processed in Facility 3,

1. Quantity increase or decrease of final product demand
   1.1. A final product is randomly selected and a random variation generated;
   1.2. A technological process that produces this product is also randomly selected;
   1.3. This process has its batch size rectified in order to accommodate the variation generated in 1.1;
   1.4. The affected flows are rectified;
   1.5. The inventory levels of all involved products are rectified;
   1.6. For each intermediate product affected by the changes in 1.5, repeat 1.2, 1.3, 1.4 and 1.5.

Fig. 5. Neighborhood move 1.

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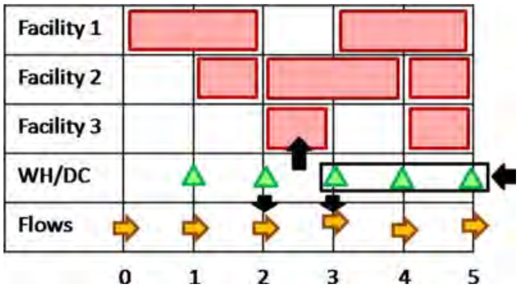

Fig. 6. Selected process.

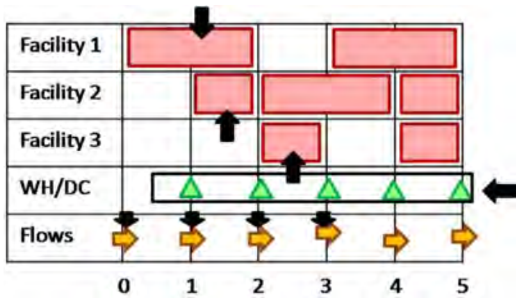

Fig. 7. Rectified processes and flows.

2. Delay or anticipate by 1 time unit the use of a technological process

2.1. An existing process is randomly selected;

2.2. Selection of the type of movement (delay/anticipation),

2.3. The change is applied and the flows rectified;

Fig. 8. Neighborhood move 2.

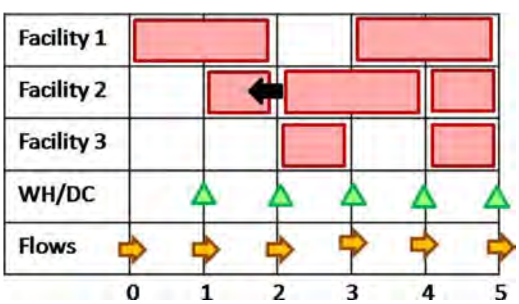

Fig. 9. Selected process.

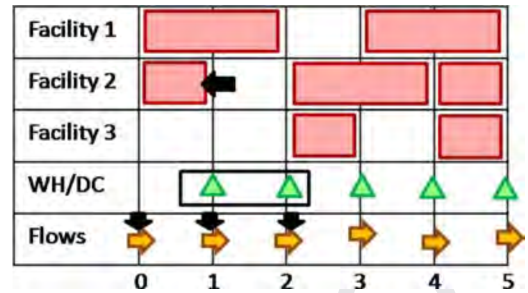

Fig. 10. Anticipated process and its flows rectified.

3. One single process is split in two equivalent ones

3.1. An existing technological process is randomly selected, under the condition that exists a facility available to use it;

3.2. The batch's selected process is split in half and the second half is allocated to the available facility;

3.3. Incoming/outgoing flows are rectified.

Fig. 11. Neighborhood movement 3 – Spliting.

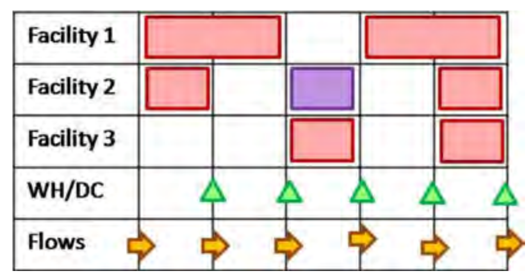

Fig. 12. Selected process.

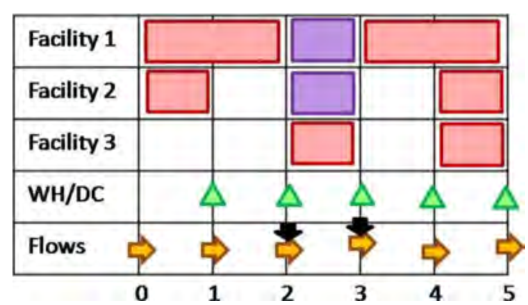

Fig. 13. Process divided and flows rectified.

consequently the algorithm selects randomly one from two possibilities and change the corresponding batch size (1.2 and 1.3). The flows taking raw or intermediate material into the selected process, at instant 2, are moving final products from Facility 3 to the WH or DC, at instant 3 have to be rectified (1.4).

Inventory levels of selected Final Product from instant 3 and onward are rectified (1.5).

Finally, if the selected process consumed intermediate products then some previous processes that generated these products have to be modified (1.6), as shown in Fig. 7.

However, to accommodate the variation generated in step 1.1, an iterative procedure between steps 1.2 to 1.5 could be necessary.

Movement 2. Delay/anticipate by 1 time unit the use of a technological process.

The delay/anticipation of a technological process is detailed in Fig. 8 and illustrated in Figs. 9 and 10. The algorithm randomly selects the process starting at instant 1 (2.1), defining an anticipative movement, shown in Fig. 9. From this movement, not only the incoming and outgoing flows, but also the inventory levels must be rectified (2.3), as shown in Fig. 10. Another, possible movement to be chosen is the process starting at instant 0, in Facility 1, which could be delayed to instant 1.

Movement 3. Two equivalent processes may be aggregated or one process may be split in two equivalent ones.

The characterization of the splitting movement is detailed in Fig. 11 and illustrated in Figs. 12 and 13, followed by the aggregation movement detailed in Fig. 14 and illustrated in Figs. 15 and 16.

The splitting movement can be done, using the starting process at instant 2, on Facility 2, which is divided into two. One process remains in Facility 2, and the other in Facility 1, at the same instant, $t = 2$, shown in Fig. 13 (3.1). Half of the batch is allocated to a new process being held at Facility 1 (3.2) and the flows are rectified (3.3).

Observe that the execution time of a process can differ from one facility to another because that depends on the technologies available

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4. Two equivalent process are aggregated

4.1. An existing technological process is randomly selected, under the condition that exists another equivalent process being held on a different facility, during the same period;

4.2. The batch's selected process is aggregated into the other equivalent process;

4.3. The selected process is extinguished;

4.4. Incoming/outgoing flows are rectified.

Fig. 14. Neighborhood move 3 – Aggregating.

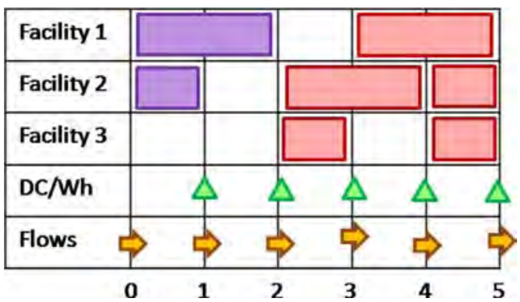

Fig. 15. Selected processes.

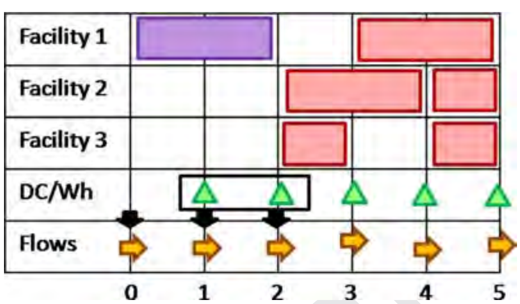

Fig. 16. Processes agglomerated and flows rectified.

5. Change facility's location

5.1. If one facility is close in one location, another one may be open in another location.

Fig. 17. Neighborhood move 4.

for each facility. Consequentially in some instances the new process created by the splitting can have a different duration than the original process.

The aggregation movement is detailed in Fig. 14, followed by its illustration in Figs. 15 and 16. The process selected to be aggregated is at Facility 2, starting at instant 0, shown in Fig. 15, (4.1). The process selected is aggregated into another equivalent process, which is in Facility 1, instant 0. In Fig. 16 the selected process is removed (4.3), and the flows and inventory levels are rectified (4.4).

Movement 4. *Change facility's location*

This movement does not affect neither transportation flows or production planning, nor the equipment design. The movement is detailed in Fig. 17 and illustrated in Fig. 18, where a random selected plant is relocated, from location A to location B.

4.2.4. Third Procedure III

In procedure (III) and, after a neighbor solution available, the algorithm will evaluate if this solution will be accepted as a new current solution, based in local search strategies, as defined in Fig. 3.

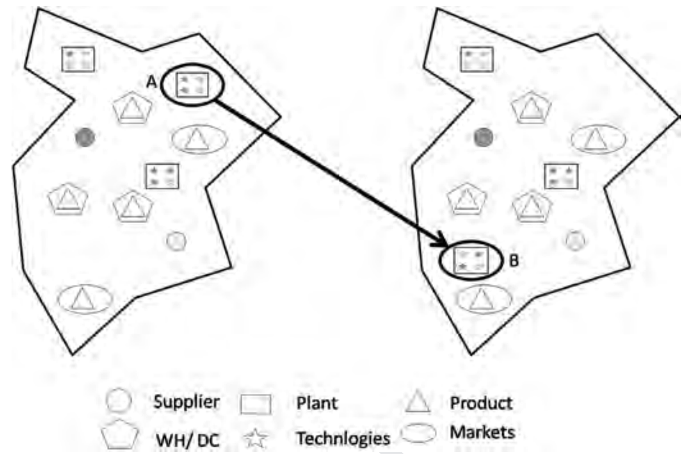

Fig. 18. Relocation of a facility.

This evaluation is based in an independent procedure, which evaluates if solution s'_i is accepted as a current solution. The procedure uses the probability of acceptance, P_{ac}, to evaluate, which depends on the adopted Local Search Strategy. The solution s'_i is randomly accepted with probability P_{ac}.

The classic SA algorithm with one objective function *f*, proposes the following acceptation probability (Kirkpatrick et al. (1983) and Černy et al. (1985)):

$$\mathbf{Pac} = \begin{cases} 1, & \mathbf{f}(\mathbf{s'i}) > \boldsymbol{f}(\boldsymbol{si}) \\ \mathbf{e}^{\frac{\mathbf{f}(\mathbf{s'i}) -- \mathbf{f}(\mathbf{si})}{\mathbf{Ti}}}, & \textbf{otherwise} \end{cases} \tag{24}$$

In each iteration, the algorithm generates a neighbor solution, s'_I, and the Local Search (LS) strategy defines the probability of acceptance of a worst solution, *Pac*.

However, in this work several local search strategies were explored, and a detailed characterization is provided by Chibeles-Martins, Pinto-Varela, Barbosa-Povoa, and Novais (2014). The simplest strategy (strategy A) explored changes in the objective function controlling Pac, at each restart. This strategy produced a suitable approximation in the lower and upper end of the PF, as the approximations are skewed towards the respective optimal values, defined in Eq. (24). However, a sparse approximation in the middle region of the Pareto Frontier (PF) was reached by this strategy.

Therefore, strategies combining both objective functions to define *Pac* procedure were explored, and the lack of middle region PF characterization was overcome, through the use of Eq. (25) (Strategy B). However, this strategy kept the Local Search exploring only the middle region of the PF.

Consequently, a LS Strategy must be expanded and should consider the both approaches simultaneously (strategies A and B), in one run to reach all PF extension.

$$Pac = \begin{cases} e^{\frac{f1(S'i) - f1(Si)}{Ti}}, & f1(S'i) \le f1(Si) \wedge \\ & \quad f2(S'i) > f2(Si) \\ e^{\frac{f2(S'i) - f2(Si)}{Ti}}, & f1\left(S'i\right) > f1(Si) \wedge \\ & \quad f2\left(S'i\right) \le f2(Si) \\ Min\left(e^{\frac{f1(S'i) - f1(Si)}{Ti}}, e^{\frac{f2(S'i) - f2(Si)}{Ti}}\right), & f1\left(S'i\right) \le f1(Si) \wedge \\ & \quad f2\left(S'i\right) \le f2(Si) \\ 1 & otherwise \end{cases} \tag{25}$$

Due to the multi-start nature of the algorithm, it is a simple procedure to change the way *Pac* is computed every time the algorithm restarts, with a new Initial Solution, on a different region of the Feasible Region.

In the proposed strategy the LS procedure is controlled 1/3 of restarts by Profit, 1/3 by Environmental Impact and the remaining by both OF simultaneously. The LS is controlled alternately by only one of the OF for a fixed number of iterations, while *Pac* is calculated by Eq. (24).

4.2.5. Fourth Procedure IV

This procedure analysis the neighbor solution efficiency during the algorithm run and, the non-dominated solutions are stored in the Pareto array. These solutions are sorted, from the highest to the lowest profit values. Due to the fact that the problem is bi-objective, all solutions in the Pareto array will be automatically sorted accordingly to f_2. For each iteration, Fig. 3 (IV), the algorithm verifies if the solution s'_i is non-dominated by comparing it with the solutions stored in the Pareto array. If is a non-dominated solution, $s'_{I,}$ is added to the array which is corrected and re-sorted using an Insertion Sort Algorithm (Cormen, Leiserson, Rivest, & Stein, 2009).

4.2.6. Fifth Procedure V

The algorithm last procedure, the restart mechanism and stop criterions control is the fifth procedure. In this work, the main goal is to define a PF and approximate it to the optimal one. This differs significantly from the classical SA algorithm, where the goal is to approximate the optimal solution.

To do that, the proposed algorithm has a multi-start procedure that allows the exploration of different regions of the PF. The algorithm restarts when both $T1_i$ and $T2_i$ are smaller than a pre-set value close to zero. Temperatures $T1_i$ and $T2_i$ are reset to their initial values $T1_0$ and $T2_0$ and a new initial solution is randomly generated by the constructive heuristic described above. The restart procedure is repeated several times and the number of restarts is determined empirically after a sensitivity analysis.

However, some parameter tuning is necessary in order to adjust the algorithm to the problem characteristics. Besides initial temperatures ($T1_0$ and $T2_0$) and the Cooling Schedule constant (α), the Stop criterion of each restart and following parameters were also adjusted empirically taking into account the following criteria:

- stop criterion of each restart;
- The number of iterations of the Multi-start mechanism.

5. Key performance indicators

In order to compare the efficiency, quality, variability and robustness of the MBSA solution, three KPI are presented and two control charts are explored and extended to engage the problem specificity.

The KPIs *D-distance* and *Size of Concave Space Covered (SCSC)* are new proposed indicators, followed by the *K-distance* indicator, which is based on Zitzler and Thiele (1999). The $\bar{X}$and R-Chart are extended through the $\bar{\bar{X}}$ *–Chart* and $\bar{\bar{R}}$ *–Chart* to guarantee the results control. It is assumed that the results are under control if the average and variability are both under control. A detailed characterization of each indicator and charts is presented. To mitigate the scaling effect both objective functions were standardized.

D-distance: *D*-distance quantifies the distance between PF obtained from the exact approach and the *MBSA* PF. The geometric representation is shown in Fig. 19 through Fig. 21.

Let *A* be a point belonging to the *MBSA* algorithm PF with coordinates ($x^S{}_{A,}$ $y^S{}_A$). Let M_i and M_{i+1} be the exact PF adjacent points of A, with coordinates ($x^M{}_{i,}$ $y^M{}_i$) and ($x^M{}_{i+1}$, $y^M{}_{i+1}$) respectively as shown in Fig. 22.

So, $x^S{}_A \in [x^M{}_{i,}\ x^M{}_{i+1}]$, and we define:

$$d_A^- = \left|y\,{}_i^M - y_A^S\right| \tag{27}$$

$$d_A^+ = \left|y\,{}_{i+1}^M - y_A^S\right| \tag{28}$$

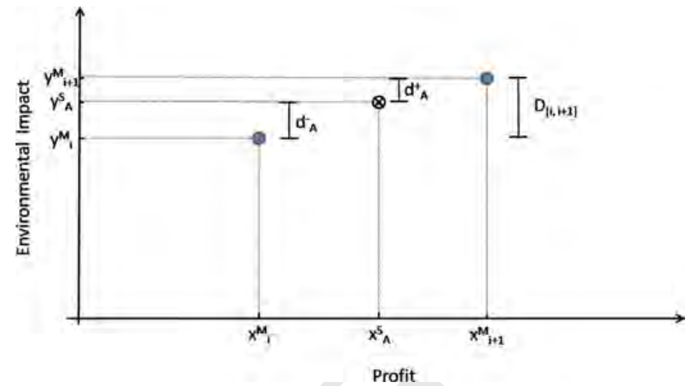

Fig. 19. Geometric representation when $D_A < 1$.

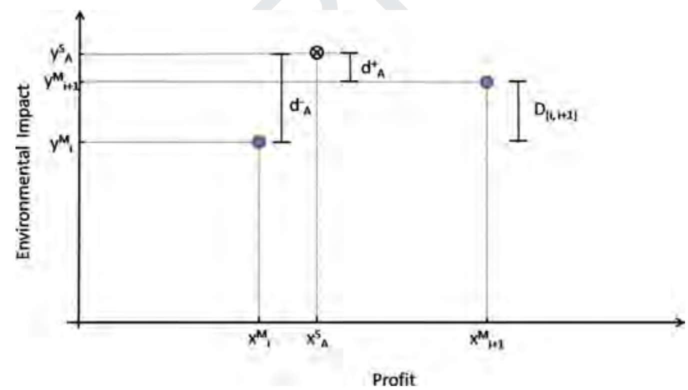

Fig. 20. Geometric representation when $D_A > 1$.

Eqs. (27) and (28) measure how distant A is from M_i and M_{i+1}, respectively, in terms of Environmental Impact, shown in Fig. 19.

The environmental impact range is defined by:

$$D_{[i,i+1]} = \left|y\,{}_i^M - y_{i+1}^M\right| \tag{29}$$

The distance of point A from *MBSA* algorithm and the exact approach PF is calculated using the expression (30):

$$D_A \begin{cases} \frac{d_A^-}{D_{[i,i+1]}}, & if\ \left|x_A^S - x_i^M\right| \le \left|x_A^S - x_{i+1}^M\right| \\ \frac{d_A^+}{D_{[i,i+1]}} & if\ \left|x_A^S - x_i^M\right| > \left|x_A^S - x_{i+1}^M\right| \end{cases} \tag{30}$$

If A is close to the exact PF front, then $D_A < 1$, as is represented in Fig. 19.

On the other hand, when A is considerable distant from the exact PF, the D_A value from Eq. (30) is $D_A > 1$, as illustrated in Fig. 20.

However, there are other situations requiring a different approach, which are going to be characterized. Consider M_0 the exact solution that minimizes the Environmental Impact Objective Function. Therefore $X^M{}_0$ is the profit value associated with solution M_0, and the *MBSA* algorithm solutions A, verifies $x^S{}_A < x^M{}_{0,}$ shown is Fig. 21. In those situations D_o and D_A are defined by Eqs. (31) and (32) and, illustrated in Fig. 21:

$$D_0 = y\,{}_0^M \tag{31}$$

$$D_A = \frac{d_A^+}{D_0} \tag{32}$$

The *D*-Distance quantification is reached through the average of $D_{A,}$ characterized by Eq. (33).

$$\mathrm{D-distance} = \frac{\sum_{A\,\epsilon\,\mathrm{SA\ FP}} D_A}{|\mathrm{SA\ FP}|} \tag{33}$$

Size of ***Concave Space Covered (SCSC):*** the SCSC development was inspired from Zitzler and Thiele (1999) and a new KPI is presented

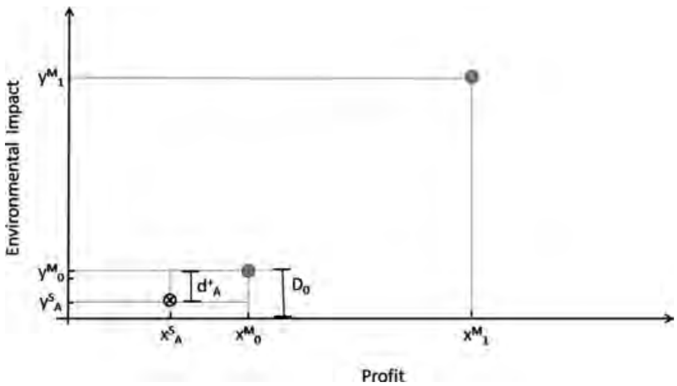

Fig. 21. Geometric representation when $x^S_A < x^M_0$.

to measure the area covered by the non-dominated solutions in the concave objective research space and consequently a concave PF (the profit maximization and environmental impact minimization have different directions). To illustrate the concept, the geometric representation is shown in Fig. 22. This measure quantifies the percentage of the exact SCSC by the *MBSA* algorithm PF.

K-distance: the *K*-distance indicator proposed by Zitzler and Thiele (1999) is used to estimate the Pareto Frontier density, by measuring the average distance of an efficient point to the *k*th nearest efficient points. This indicator allows sparse PF identification vs a high saturated PF.

The *K*-distance aim is the density comparison in the two approaches. In this work is justified a value of $K = 4$, to avoid the use of more than half of its elements in the exact quantification.

5.1. Control charts

The $\bar{\bar{X}}$ –*Chart* and the $\bar{\bar{R}}$ –*Chart* give to the decision maker complementary information. The former is focused on the constancy of the average value and the latter is specially designed for detecting changes in variability. These charts are characterized through an Upper Control Limit (UBL), Lower Control Limit (LBL) and an average value definition. The data will float around the average value and if remains inside the boundaries, the algorithm is considered robust and stable based on $\bar{\bar{X}}$ –*Chart* and $\bar{\bar{R}}$ –*Chart* respectively.

The control charts were derived considering KPI *D*-distance, using *nk* observations from *n* Pareto frontiers. Each PF defines a subgroup of distance and range values, so its average can be obtained, $\bar{\bar{X}}$ and $\bar{\bar{R}}$, respectively. However to analyze the algorithm robustness, a sensitive analysis is undertaken defining subgroups of data, triggering the control-chart for the $\bar{\bar{X}}$ and for $\bar{\bar{R}}$ characterization. Making use from the Central Limit effect the Normal distribution can be assumed and the respective control charts are derived (Eqs. 34 and 35).

$$UCL_{\bar{\bar{X}}} = \bar{\bar{X}} + zS_{\bar{X}} \quad \text{and} \quad LCL_{\bar{\bar{X}}} = \bar{\bar{X}} - zS_{\bar{X}} \tag{34}$$

$$UCL_{\bar{\bar{R}}} = \bar{\bar{R}} + zS_{\bar{R}} \quad \text{and} \quad LCL_{\bar{\bar{R}}} = \bar{\bar{R}} - zS_{\bar{R}} \tag{35}$$

6. Instance characterization

To illustrate the *MBSA* application a case study is used. The KPI measures are explored and the case study instance supports a sensitive analysis.

The SC operates with two production sites (A and B) and one centralized supplier. Each one of these production sites has the possibility of installing three types of multipurpose technological resources (TP1, TP2 and TP3) to produce 12 different products. TP1 produces six final products (P1 to P6), TP2 and TP3 three products each (P7 to P9 and P10 to P12, respectively), shown in Table 1. The maximum capacity associated to the facilities' technologies is shown in Table 1, while in Table 2 is shown the demand for each market, using a multiproduct DC. Fig. 23 illustrates the SC superstructure.

Table 1
Facilities suitability technological resources and capacities.

Facilities	Technological process	Capacity (Tonnes)	Final products
Site A	TP1	85	P1, P2, P3, P4, P5, P6
	TP2	45	P7, P8, P9
	TP3	25	P10, P11, P12
Site B	TP1	65	P1, P2, P3, P4, P5, P6
	TP2	25	P7, P8, P9
	TP3	25	P10, P11, P12

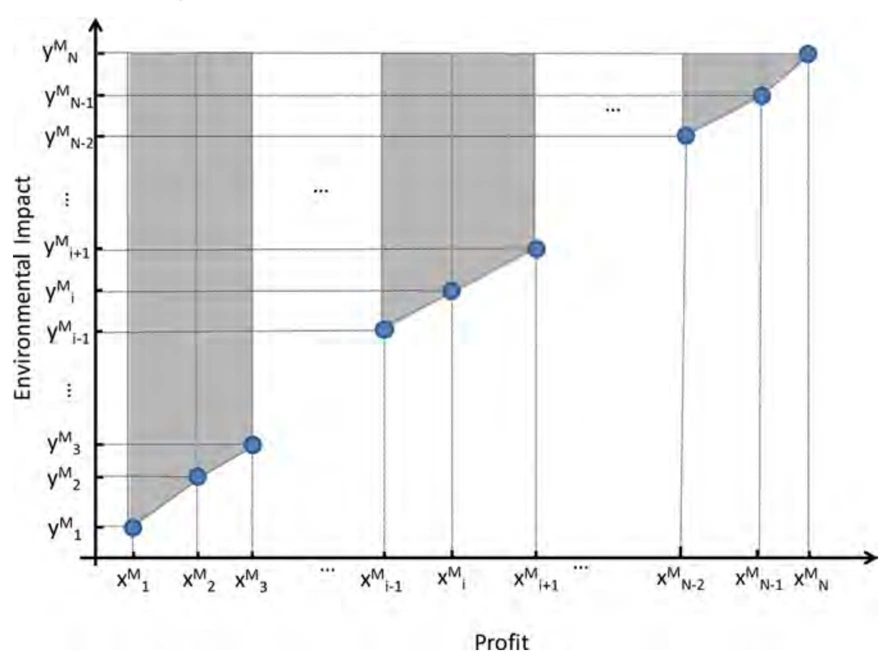

Fig. 22. Size of Space Covered representation.

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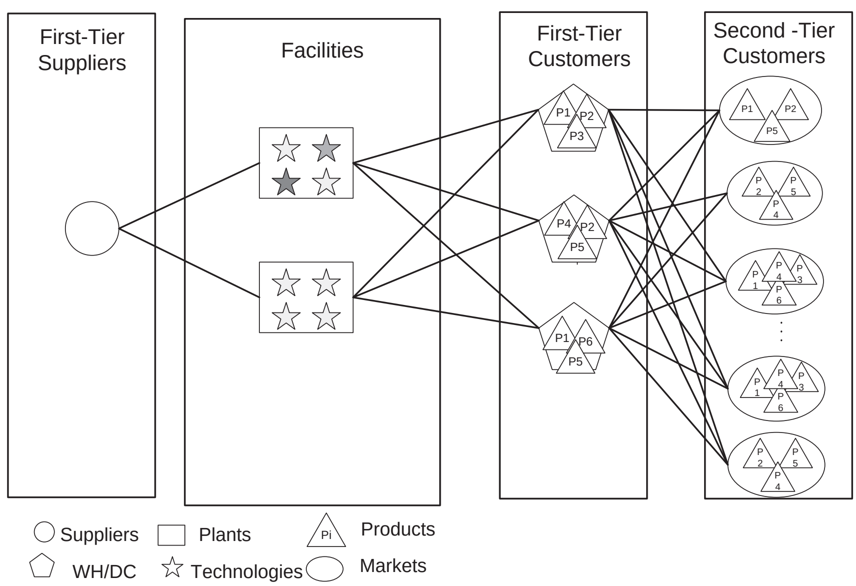

Fig. 23. Supply chain illustration for the second instance.

Table 2
Annual range product demand for each market.

Product	Market	Demand for each product (max Tonnes)
P1-P6	M1	200
	M2	260
P7-P9	M3	200
	M4	140
P10-P12	M5	100
	M6	80

Table 3
Pollutants emitted per utility consumption (Duque, Barbosa-Povoa, & Novais, 2010).

Utility	CO	CO2	NOx	Sox	Units
Diesel	14.828	2609.5	34.6	–	kg/m3
Electricity	4.151e–3	7.306e–1	1.941e–3	3.872e–3	kg/kwh

Table 4
Damage to human health (Geodkoop & Spriensma, 2001).

Damage	CO	CO2	NOx	SOx
Human health (DALYs/kg emission)	–	7.5e–4	8.74e–5	5.35e–5

It is assumed that for each technological resource, some electricity consumption will occur, generating an associated environmental impact. Also environmental impacts related to transportation, namely CO2, NOx and SOx emissions, are considered. The corresponding data are given in Table 3. The transportation costs are not only geographical distance dependent, but also transported load depend. An assumption of full truck load freights at an average speed of 80 km/h is used.

The environmental impact quantification is based on the Eco-indicator 99, focused on the Human Health (HH) damage, Table 4.

7. MBSA algorithm results analysis

In order to assess the algorithm results quality, robustness and stability not only a comparison with the exact approach was performed, but also, a sensitivity analysis is developed. For each analysis a variations of $\Delta_{I,}$ ranging from −5% to +5%, with 1% increments were applied, over the parameters: TP1 and TP2 technology capacity in site A and B, respectively; and demands of product P12 for M5 and M6 Market.

The reason for those parameters selection results from the need to explore its impact in algorithm behavior, like: the algorithm solution impact when the most relaxed technology capacity suffers disturbance, over TP1; the annual production planning behavior when variation of the lowest technology capacity available occur, over TP2; and what happens to the production and transportation planning through product demand variation. Nevertheless, some of those algorithm results are compared with the exact approach.

Beyond that, with the aim to compare the solution efficiency approach of the *MBSA* algorithm, three KPI measures and two control charts: *D*-distance, *K*-distance, SCSC, $\overline{\overline{X}}$ −*Chart* and $\overline{\overline{R}}$ −*Chart* were used.

The multi-objective approach requires a set of solutions to characterize the efficient frontier, the ability of each method to find those solutions are defined by the quantity of non-dominated solutions obtained. The number of non-dominated solution of MBSA over each parameter variation is summarized in Table 5. As the literature stated the exact approach is time-consuming, and this case was no exception.

The computational time required for those solutions, over each *MBSA* and the exact approaches' run are shown in Table 6 and a comparison analysis in Table 9. The MB*SA* algorithm presents, on average a time improvement around 95% when compared with the exact approach and defines an efficient frontier with a higher number of non-dominated solutions.

An important aspect to analyze in the algorithm is the quality of the obtained solutions. This is done through the comparison of the area coved defined by the efficient frontiers of both approaches. The higher % of exact area covered by the MBSA algorithm more quality solutions are defined. The comparison of the % of exact area covered by MBSA was quantified by the SCSC KPI. Its comparison shows the ability of MBSA to cover more than 70% of the exact area as shown in Table 7.

Another important aspect to qualify the solutions reached is its density. Based on Zitzler, Laumanns, and Thiele (2001), the KPI *K*-distance was applied. The *K*-distance KPI quantify the density of non-dominated solution in the PF and characterize the distance between the *k*th nearest non-dominated solutions, with $K = 4$, meaning the lower the distance among solution, the higher its density and, a higher PF characterization is achieved. From Table 8 it is shown that

Table 5
Quantity of non-dominated solutions for each run for the MBSA algorithm approach.

	−5%	−4%	−3%	−2%	−1%	0%	+1%	+2%	+3%	+4%	+5%	Average
TP 1	3154	2410	3090	2147	2544	2775	2735	2316	2985	2860	2754	2706,4
TP2	2628	3119	2806	3000	2790	2775	3830	2434	2329	2628	3225	2869,5
P12 in M5	2968	2623	3079	3000	2869	2775	3307	2956	3160	2904	2347	2908,0
P12 in M6	3110	3099	2282	3408	2955	2775	3276	2705	2950	2818	2707	2916,8

Table 6
Time for each run in both approaches (CPU seconds).

		−5%	−4%	−3%	−2%	−1%	0%	+1%	+2%	+3%	+4%	+5%
TP 1	Exact	15326	16451	18531	14016	12744	78708	23426	34646	12753	24243	20788
	MBSA	1383	1255	1451	1440	1020	1389	1207	1221	1464	1254	1478
TP 2	Exact	10563	15104	15016	16389	25623	78708	15450	18412	14318	30878	14105
	MBSA	1691	1476	1091	1275	1291	1389	1219	1269	1299	1203	1415
P12 in M5	Exact	13027	19162	11212	18281	19782	78708	36072	16120	16435	12131	25077
	MBSA	1236	1180	1185	1180	1145	1389	1222	1322	1160	1250	1244
P12 in M6	Exact	23770	21850	32637	11629	22745	78708	15916	14868	17587	15447	19275
	MBSA	1372	1412	1144	1258	1202	1389	1358	1217	1136	1085	1138

Table 7
Percentage of SCSC.

	−5%	−4%	−3%	−2%	−1%	0%	+1%	+2%	+3%	+4%	+5%	Average
TP 1	77,0	76,6	73,5	74,1	74,0	74,0	75,5	74,8	73,3	74,4	75,2	74,8
TP 2	76.6	76.3	75.3	71.7	74.9	74.0	73.9	72.4	72.0	72.8	71.2	73.7
P12 in M5	70,9	69,5	72,2	70,3	70,1	74,0	71,9	70,9	70,9	67,0	72,6	70,9
P12 in M6	73,3	73,7	71,6	70,7	71,6	74,0	70,8	71,0	70,0	69,9	69,4	71,5

Table 8
K-distance measures from the MBSA and exact approach.

		−5%	−4%	−3%	−2%	−1%	0%	+1%	+2%	+3%	+4%	+5%	Average
TP1	Exact	915,2	913,3	923,1	925,1	927,8	929,6	931,2	932,1	933,6	935,1	938,0	927,6
	MBSA	3,14	4,08	4,05	4,55	4,56	3,53	3,63	4,24	4,25	3,50	3,58	3,92
TP2	Exact	923,2	923,2	925,5	923,0	925,8	929,6	930,2	928,4	930,2	933,9	934,1	927,9
	MBSA	3,792	3,193	3,555	3,381	3,560	3,534	3,519	4,074	4,242	4,225	3,733	3,710
P12 in M5	Exact	928,9	926,6	923,1	928,6	928,7	1028,5	927,3	929,0	928,6	935,6	925,6	937,3
	MBSA	3,506	3,655	3,696	3,253	3,354	3,534	3,379	3,286	3,231	3,316	4,138	3,486
P12 in M6	Exact	928,7	926,6	928,2	928,8	927,2	929,6	927,8	929,8	927,6	926,9	930,5	928,3
	MBSA	4,146	3,139	4,240	4,175	3,273	3,534	3,258	3,567	3,532	3,406	3,548	3,620

Table 9
Comparision analysis.

		Time average	% Time improvement	*K*-Distance	% *K* improvement
TP1	Exact	26 650		927,6	
	MBSA	1324	95	3,92	99.5
TP2	Exact	23142		927,9	
	MBSA	1329	94	3,710	99.6
P12 in M5	Exact	24182		937,3	
	MBSA	1228	95	3,486	99.6
P12 in M6	Exact	24948		928,3	
	MBSA	1247	95	3,620	99.6

the values from the *MBSA* algorithm are much lower than the exact approach results. On average the *MBSA* has a *K*-distance around 3,7 compared with 930 in the exact approach, showing a much higher density PF characterization in the MBSA approach. The reason of higher solution results in the exact approach is from the model complexity and computational burden strive the definition of non-dominated solutions. Once more the MBSA algorithm presents a better performance and is shown an improvement around 99 %, shown in Table 9.

Finally, the algorithm solutions variability and robustness are analyzed using the proposed KPI *D*-distance over eight control diagram $\bar{\bar{X}}$ *–Chart* and $\bar{\bar{R}}$ *–Chart*, two control diagram for each analyzed parameter, respectively. To summarize such information, data aggregation was performed, and the four $\bar{\bar{X}}$ *–Chart* were aggregated into one, shown in Fig. 24. The same procedure was adapted for $\bar{\bar{R}}$ *–Chart*, resulting Fig. 25.

The charts characterization requires the upper and lower control limits quantification, $UCL_{\bar{\bar{X}}}$, $LCL_{\bar{\bar{X}}}$, $UCL_{\bar{\bar{R}}}$ and $LCL_{\bar{\bar{R}}}$, based on Eqs. (34) and (35). Two levels of control were characterized for the aggregated information, one tighter than the other. In the Figures, the higher control is characterized by the range [LCL_{Max}, UCL_{Min}], and the more relaxed control, the solution may float in the range [LCLMin, UCLMax]. The algorithm is considered robust and stable if the *D*-distances remains between its upper and lower control limits, [LCLi, UCLi].

As can be seen in Fig. 24, the algorithm solution robustness is characterized and all the solution remains between the thigh boundaries, except one solution which is within the relaxed boundaries.

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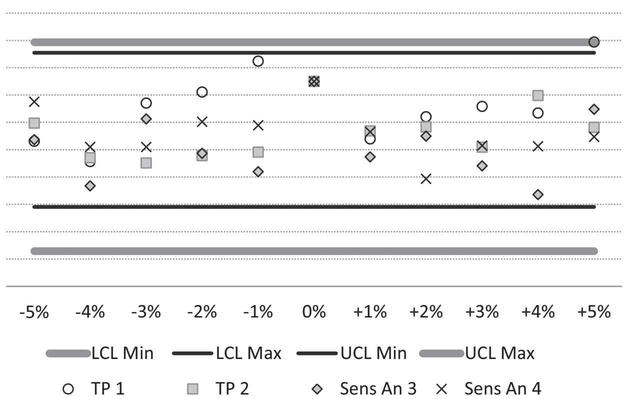

Fig. 24. Average control limit.

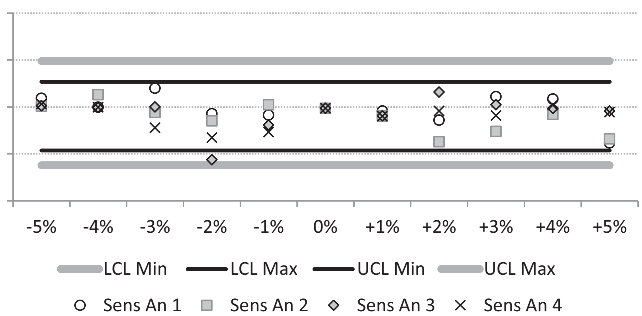

Fig. 25. Variability control limit.

The algorithm solution variability is analyzed in $\bar{\bar{R}}$ *–Chart*, shown in Fig. 25. This chart quantifies the difference between the smallest and largest values in the sample, reflecting the solution variability instead of the tendency towards a mean value, like the $\bar{\bar{X}}$ *–Chart*.

The algorithm solutions variability suggests a steady state trend in the variability values, indicating a steady and narrowed variability. This trend would reflect on the $\bar{\bar{X}}$ *–Chart*, by mean values closer to the chart center, and within limits. Based on the control charts the algorithm solution shows a robust and stable performance.

8. Conclusion

In this work a problem with increasing importance in the supply chain area has been addressed, the so called green supply chain design and planning. Economic but also environmental objectives are accounted when designing and planning supply chains aiming at establishing tradeoffs between the traditional profit objective and such systems environmental impact. Due to the recognized difficulties that arise when solving these problems through the most common published approaches, exact approaches, the present paper proposes an alternative solution approach based on a meta-heuristic that has proved to be promising and could consequently constitute the base of an expert system application to support the decision making process within such problems.

This approach is a Bi-objective Simulated Annealing approach, MBSA, which is developed under a constructive heuristic that guarantees solution's stability, feasibility and robustness. The algorithm involves four different types of Neighborhood movements where a multi-start local search strategy taking advantages of both objective functions was implemented. The algorithm performance was measured against an exact approach through the analysis of a set of defined generic key performance indicators where the algorithm solutions quality, based on the distance between the proposed algorithm Pareto frontier and the exact Pareto frontier were considered.

In addition to validate the proposed solution algorithm a sensitivity analysis was performed and the resulted KPI values were analyzed and discussed.

The results show that the MBSA proved to be an efficient and powerful heuristic alternative when compared with exact methods providing the definition of the Pareto Frontier of Supply Chain Network Design and Planning problems. Different trade-offs along the Pareto Frontier were obtained informing the decision maker with the necessary results to support his/her decisions. However the PF generated by the algorithm is composed with solutions obtained approximately. Without the exact PF it is not possible to assess the distance between the algorithm solutions and the real efficient frontier. In addition, as the methodology is based on a Metaheuristic the algorithm's parameters tuning is always implied every time a new problem instance is studied.

As future developments, different aspects should be explored. First of all the algorithm should be tested in more complex instances. A benchmarking analysis could be developed using the proposed KPI performance indicators. In addition, and on the algorithm performance it is important to explore the impact of using different heuristics with greedy components in all or at least some of the restart mechanisms. Furthermore it will also important to extend the developed approach to account with other important supply chain aspects such has the treatment of the social objective when designing such systems aiming at establishing sustainable supply chains. Other aspects could also be incorporated in this algorithm extension has risk measures and uncertainty presence.

Uncited references:

Kirkpatrick, J., & Vecchi, 1983

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