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Supply chain network optimization using a Tabu Search based heuristic

Otimização da rede de uma cadeia de suprimentos com a utilização de uma heurística baseada em Busca Tabu

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Abstract: This paper discusses the implementation and evaluation of a heuristic based on Tabu Search to optimize a supply chain network. To this end, a single-source model proposed by Farias & Borenstein (2012) was implemented. The problem was solved by adapting the Lee & Kwon method (2010), exchanging distribution centers (DCs) and arcs to find the lowest cost for a supply chain network. Twenty-two instances proposed by Farias & Borenstein (2012) were solved and the results indicate that, for the scenarios, the method applied presented good computational performance, obtaining results with 81.03% reduction of the average processing time. However, there was an increase of 4.98% in the average cost of the solutions obtained through the heuristic method when compared with the optimal results. Finally, the problem was solved for four other instances with real features, proving the efficiency of this heuristic for large-scale problems, considering that all solutions were obtained in less than 2 minutes of processing.

Keywords: Supply chain network optimization; Supply chain management; Heuristic; Tabu Search.

Resumo: *Este artigo discute a implementação e avaliação de uma heurística baseada em Busca Tabu para otimizar uma rede de cadeia de suprimentos. Para tanto, o modelo single-source proposto por Farias & Borenstein (2012) foi implementado. O problema foi resolvido por uma adaptação do método de Lee & Kwon (2010), substituindo centros de distribuição (CDs) e arcos a fim de encontrar o menor custo para uma rede de cadeia de suprimentos. Foram resolvidas as 22 instâncias propostas por Farias & Borenstein (2012) e os resultados indicam que, para esses cenários, o método aplicado teve um bom desempenho computacional, obtendo resultados com uma redução de 81,03% no tempo médio de processamento. Contudo, houve um aumento de 4,98% no custo médio das soluções obtido pelo método heurístico quando comparado com os resultados ótimos. Por fim, o problema foi resolvido para outras quatro instâncias com características reais, comprovando a eficiência da heurística para problemas de grande escala, visto que todas as soluções foram obtidas em menos de 2 minutos de processamento.*

Palavras-chave: *Otimização de rede de cadeia de suprimentos; Gestão da cadeia de suprimentos; Heurística; Busca Tabu.*

1 Introduction

Recently, companies's supply chains have grown significantly, including production and distribution locations around the world and, at the same time, increased global competition has generated a strong demand for new decision support tools in strategic, tactical and operational levels (Almeder et al., 2008).

The great challenge of supply chain management is the need for quickly (and reliably) materials and

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products handling between company and customers without losing competitiveness (Viana et al., 2014). However, this movement is not linear because, many times, it is a path through different countries to reach the final destination. Thus, the supply chain management must deal with several functions, such as transport, distribution and information technology (IT), aiming to optimize the production and delivery of products to supply chain members (Rezende et al., 2002). Altiparmak et al. (2006) consider that companies must maintain high customer service levels and at the same time, are forced to reduce their costs and to remain with the same profit margins.

Beamon (1998) points out that, for years, many researchers and practitioners have individually investigated the various processes of the supply chain; however, recently, there has been growing interest in performance, design and analysis of the chain as a whole (Visentini & Borenstein, 2014). This growing interest is explained by the need for integrated view of supply chain management. In addition, research and analysis of the logistics chain techniques are more mature, allowing a more detailed analysis and even taking into account a larger number of variables related to key issues of supply chains, such as cost, speed and price (Poli & Pureza, 2012). Consequently, Operations Research (OR) techniques are being increasingly used for supply chain management (Melo et al., 2009).

In a supply chain, the flow of goods between suppliers and customers goes through several stages, which consist of different facilities (Sabri & Beamon, 2000), i.e: service centers, factories, warehouses or depots. In general, the design of a supply chain network begins with the identification of potentially interesting sites that may be able to support the skills needed for new installations. The main objective of the problem is to determine the location of facilities so that the sum of the fixed costs of opening new facilities and variable costs of assigning customers to certain demands in already operating facilities is minimized (Tragantalerngsak et al., 1997).

Ombuki et al. (2006) suggest that in cases where the models become more complex, they can be solved not only by exact techniques, but, for instance, using meta-heuristics in order to find approximate solutions in polynomial time, rather than high costs exact solutions, adjusting to the resolution of complex problems.

Among the metaheuristics, one of the most proeminents is the Tabu Search (TS), a technique that uses strategic exploration and flexible memory as a guide in search for a space solution (Arenales et al., 2007), determining the direction of the search based on the properties of the current solution and its history. The method has a memory for visited solutions, preventing inferior solutions to those already found to be revisited.

Considering the need to reduce logistics costs and the complexity of problems with real instances, the aim of this paper was to implement and evaluate a Tabu-Search-based heuristic to optimize a supply chain network.

In order to describe the problem in greater detail, present the method used for its solution, and the results obtained, this article is divided into five sections. In the introduction we considered the context, justificative and objective of the study. The second section consists of literature review, addressing the supply chain design and heuristic methods. Next, we discuss the methodological procedures adopted in the research, detailing the problem solved and heuristics used for its solution. In the fourth section we present and discuss the results of the research. Finally, section 5 presents conclusions of the research.

2 Literature review

2.1 Supply chain network design

The supply chain network design is one of the most comprehensive issues related to supply chain management, involving decisions on operational, tactical and strategic levels. This problem involves determining the number, location and capacity of the facilities, establish distribution channels and flows of materials and products that will be produced and sent to suppliers in each consumption layer.

In general, to solve this kind of design problem, the network is broken down into subproblems. Mathematical models and solution methodologies for each subproblem are then developed and later integrated (Elhedhli & Gzara, 2008). The first subproblem is the network of all raw material suppliers, parts and services to the factories. The second sub-network includes the factories where the final products are manufactured. The final products are shipped from factories to retailers through distribution channels, using distribution facilities, such as warehouses and distribution centers.

The project therefore involves the calculation of the total costs of an installation, including the fixed costs of opening facilities, the transportation costs associated with flows of materials and products, the costs of materials supply and storage costs and movement of materials and products (Wu et al., 2006).

Cordeau et al. (2008) report that following the seminal work on multi-commodity distribution network design by Geoffrion & Graves (1974), a large number of models have been proposed for the supply chain design, incorporating natural resources, production and transport aspects (Visentini & Borenstein, 2014). Considering the large number of variables and constraints, this problem is classified as NP-hard, for which many exact and heuristic algorithms have been developed in recent decades (Wu et al., 2006). Kazemi et al. (2008) points out that many researchers have addressed the optimization of supply chain networks, which cover a wide domain formulations ranging from the most simple, for a single product, to more complex models, nonlinear or stochastic. With this kind of complexity, it becomes necessary to use heuristics or meta-heuristics to solve these models.

2.2 Heuristic methods

Zaleta & Socorrás (2004) say there is no algorithm capable of solving in optimality the problem of supply chain design for large instances, within a reasonable period of time. Lee & Kwon (2010) add that although computing power has increased, and a number of efficient and powerful software to handle large programming is offered in the market, the computational time for troubleshooting with hundreds of products and customers, and dozens of plants, it is still very heavy. According to the authors, in practice the decision on distribution centers operation are evaluated taking into consideration various analysis scenarios and it is desirable that the computational time to solve each scenario does not exceed thirty minutes.

Chart 1 presents some of the studies that have developed heuristics to optimize supply chain networks. This resolution approach is therefore important when networks are very complex and involve many variables and data, being difficult or even impossible, to obtain an optimal solution to the problem.

Chart 1. Heuristics approaches to supply chain network optimization.

	REFERENCE	PROBLEM	HEURISTIC APPROACH
1	Pirkul & Jayaraman (1996)	Minimizing the costs of a multi-commodity single-source network	Lagrangian relaxation
2	Holmberg & Hellstrand (1998)	Global optimum resolution of a multimodal supply chain network design with non capacitaded facilities	Lagrange in a branch-and-bound structure
3	Jayaraman & Pirkul (2001)	Minimizing the costs of a single-source network with several stages	Lagrangian relaxation
4	Altiparmak et al. (2006)	Find a set of best possible solutions for optimization of a network design of a multi-objective supply chain	Genetic Algorithms and Simulated Annealing
5	Cordeau et al. (2006)	Solving a problem of supplier selection, location of factories and warehouses and the flow of goods across the network	Branch-and-bound method and Bender's decomposition
6	Lee et al. (2008)	Resolving a distribution planning problem for a multi-level supply chain network	Tabu Search
7	Li et al. (2009)	Determining the location of capacitated plants incorporated into a problem of multi-commodity flow	Lagrange, subgradient optimization and Tabu Search
8	Amrani et al. (2009)	Multi-commodity extension in two stages to the single-source capacitated facility location problem	Search method in the neighborhood integrated with a tabu procedure
9	Bidhandi et al. (2009)	Network design of a network of multi-commodity supplies in a single period	Bender's decomposition
10	Hsu & Li (2009)	Design a company's supply network, seeking to exploit the economies of scale of impacts arising from the use of optimal capacity and the amount of production of each facility	Heuristic based in Simulated Annealing
11	Javid & Azad (2010)	Simultaneous optimization of location, allocation, capacities, inventory and routing in a chain of stochastic supplies, where each client has an uncertain demand, and each CD has certain amount of safety stock	Tabu Search and Simulated Annealing

Source: elaborated by the authors.

Chart 1. Continued...

	REFERENCE	PROBLEM	HEURISTIC APPROACH
12	Yao et al. (2010)	Location-allocation problem of facilities and stocks, allowing the use of multiple sources of warehouses	Iterative heuristic method using approach and transformation techniques
13	Shimizu & Fujikura (2010)	Strategic optimization of a logistics network design to improve the efficiency of a supply chain	Hibrid Tabu Search
14	Lee & Kwon (2010)	Facilities location problem and a distribution plan in a single-source network	Tabu Search
15	Kim & Kim (2010)	Determining the location of patient care facilities with the aiming to balance the number of patients assigned to facilities	Branch and bound
16	Asken & Aras (2012)	Location of facilities with fixed charges for planning a system to provide public services to consumers.	Tabu Search
17	Sun (2012)	Capacited facility location	Tabu Search
18	Badri et al. (2013)	Design and strategic and tactical planning of a network of supply chains	Lagrangean relaxation
19	Addis et al. (2013)	Solve a generalization of the facility location problem in which two levels of facilities should be located	Neighborhood search
20	Rahmani & Mirhassani (2014)	Where to locate the facilities and how to move commodities to minimize costs	Genetic algorithm
21	Li et al. (2014)	Location of multi-product facilities. Minimize costs, allocating deposits, determining the flow of products in plants, opening distribution centers to other customers.	Lagrangian Relaxation and Dantzig-Wolfe
22	Arrondo et al. (2015)	Bi-objective facilities location.	FEMOEA, Evolutionary algorithm
23	Ho (2015)	Determine a subset of enabled facilities to be opened in order to meet the demands of customers so that the costs are minimized.	Tabu Search

Source: elaborated by the authors.

Different heuristics were applied from methods based on integer linear programming to meta-heuristics, as we can see in Chart 1. Considering the simplicity of the method and the results obtained, the Tabu Search was implemented in this article due to its simplicity and its ability to find very close to optimal solutions in a very small computational time (Pepin et al., 2008). Even though a relatively new technique, results in complex problems are usually extremely promising (Colin, 2007). Due to these facts and to its great adaptation to optimization problems of supply chain networks (Glover, 1989), this technique has been successfully applied to various problems with thousands and even millions of integer variables, finding very similar solutions to the global optimum, including problems of logistics such as location, transportation, supply chain network design, vehicle routing and distribution (Keskin & Uster, 2007).

Tabu Search is a local search meta-heuristic introduced by Glover (1986) that seeks to improve a current solution by executing movements within a neighborhood (Chiang et al., 2009). The TS explores the space of a problem solution moving, at each iteration, the current solution to its best neighbor and to avoid cycles, some attributes of the current solution is stored in a list and any solution that has the same attributes is declared as prohibited (or taboo) for a given number of iterations (Gendreau et al., 1999), aiming to prevent the occurrence of the search cycles (Amrani et al., 2009).

3 Methodological procedures

3.1 Problem definition

The supply chain analyzed in this article consists of raw material vendors, production plants (factories), DCs and product consumption areas (customers).

The plants are responsible for producing a set of rubber-based products. These products have various sizes, properties and different specifications, however, are basically composed of the same raw materials. The plants are supplied by different providers. DCs receive goods from any factory, sending customers the quantities of each product according to the demand.

A factor of great impact in minimizing the total cost of the supply chain is the transportation between nodes. It is therefore necessary to consider the transport costs of raw materials (from vendors to factories) and finished products (from factories to customers, through the DCs). Because of the quantity of products involved in the flow, it is also necessary to consider the production capacity limiters on each factory and processing in DCs and other fixed and variable costs of each facility.

The location of vendors, factories, DCs, and customers are known, and the purpose of this problem is to determine the set of DCs to be open so that the company can fully meet the demand of its customers the lowest possible cost. Therefore, it is necessary to consider the quantities of all raw materials to be purchased from each supplier and the quantity to be produced at each site. Regarding the distribution strategy, the problem considering a single-source approach, where each customer can only receive products coming from a single DC.

3.2 Formulation

To build the model, Arenales et al. (2007) suggest that the problem should be "translated" in logical relations simulation, mathematical or a combination of both. To solve this problem we used the single-source model proposed by Farias & Borenstein (2012), where a demand area may be supplied only for a single CD. The sets used in the model are shown in Chart 2 and the decision variables of the model in Chart 3.

Parameters used in the model are shown in Chart 4.

The mathematical model used is formulated as follows:

$$\begin{aligned}\min \sum_{w\in W} CT^{o}_{w} z_{w} + \sum_{w\in W}\sum_{c\in C}\sum_{s\in S} CT^{g}_{w} d_{sc} g_{wc} + \sum_{f\in F}\sum_{w\in W}\sum_{s\in S} CT^{p}_{fs} x_{fws} + \\ \sum_{v\in V}\sum_{f\in F}\sum_{r\in R} CT^{t}_{fvr} y_{vfr} + \sum_{f\in F}\sum_{w\in W}\sum_{s\in S} CT^{t}_{fws} x_{fws} + \sum_{w\in W}\sum_{c\in C}\sum_{s\in S} CT^{t}_{wcs} d_{sc} g_{wc}\end{aligned} \quad (1)$$

Subject to

$$\sum_{w\in W} g_{wc} = 1 \qquad \forall\, c\in C \quad (2)$$

$$\sum_{c\in C}\sum_{s\in S} d_{sc} g_{wc} \le CAP_{w}\, z_{w} \qquad \forall\, w\in W \quad (3)$$

$$\sum_{w\in W} z_{w} \le U_{w} \quad (4)$$

$$\sum_{c\in C} d_{sc} g_{wc} \le \sum_{f\in F} x_{fws} \qquad \forall\, w\in W, \forall\, c\in C, \forall\, s\in S \quad (5)$$

$$\sum_{f\in F} y_{vfr} \le CAP_{vr} \qquad \forall\, r\in R, \forall\, v\in V \quad (6)$$

$$\sum_{w\in W}\sum_{s\in S} u_{rs} x_{fws} \le \sum_{v\in V} y_{vfr} \qquad \forall\, r\in R, \forall\, f\in F \quad (7)$$

$$\sum_{w\in W}\sum_{s\in S} u_{s} x_{fws} \le CAP_{f} \qquad \forall\, f\in F \quad (8)$$

$$\sum_{f\in F}\sum_{s\in S} x_{fws} \ge u_{min} \qquad \forall\, w\in W \quad (9)$$

$$z_{w} \in \{0,1\} \qquad \forall\, w\in W \quad (10)$$

$$g_{wc} \in \{0,1\} \qquad \forall\, w\in W, \forall\, c\in C \quad (11)$$

The objective function of the Model 1 seeks to minimize the sum of annual costs of DCs, DC's processing, production in factories, transportation of raw materials to factories and finished products to customers, through the DCs. The single-source approach is expressed in 2, where it is guaranteed that each customer will be attended only by a single DC. Constraint 3 ensures that the DC capacity is not violated, while 4 limits the number of DCs to install. Constraint 5 ensures that the DCs have the

Chart 2. Sets used in the model.

W ***F***	set of DCs; set of factories;
S ***R***	set of products; set of raw materials;
V ***C***	ser of vendors; set os customers.

Source: adapted from Farias & Borenstein (2012).

Chart 3. Decision variables of the model.

x_{fws}	quantity of product $s \in S$ shipped from factory $f \in F$ to DC $w \in W$
y_{vfr}	quantity of raw material $r \in R$ shipped from vendor $v \in V$ to factory $f \in F$
z_{w}	binary variable, where: 1 if the DC $w \in W$ is selected; and 0 otherwise
g_{wc}	binary variable, where: 1 if the DC $w \in W$ meets the demand of the consumer area $c \in C$; and 0 otherwise

Source: adapted from Farias & Borenstein (2012).

Chart 4. Parametes used in the mathematical model.

d_{sc}	demand of products $s \in S$ by the customer $c \in C$;
U_w	maximum of DCs that can be opened;
u_{rs}	utilization rate of raw material $r \in R$ per unit of product $s \in S$;
u_s	utilization rate of production capacity per unit of product $s \in S$;
CAP_w	transfer capability of DC $w \in W$;
CAP_{vr}	supply capacity of raw material $r \in R$ by supplier $v \in V$;
CAP_f	production capacity of factory $f \in F$;
CT_w^o	annual fixed cost of operation of DC $w \in W$;
CT_w^g	unit cost transfer of DC $w \in W$;
CT_{fs}^p	unit cost of production of product $s \in S$ at the factory $f \in F$;
CT_{fvr}^t	unit cost of transportation of raw material $r \in R$ from supplier $v \in V$ to factory $f \in F$;
CT_{fws}^t	unit cost of transportation of product $s \in S$ from factory $f \in F$ to DC $w \in W$;
CT_{wcs}^t	unit cost of transportation of product $s \in S$ from DC $w \in W$ to customer $c \in C$;
u_{min}	minimum demand for opening DC $w \in W$.

Fonte: adapted from Farias & Borenstein (2012).

capacity to meet demand, while 6 ensures that the supply capacity of raw material by the supplier is respected. In 7 is established the relationship between raw materials and products. The Constraint 8 ensures that the capacity of the plants will not be violated and 9 determines a minimum use so that a DC can be installed. Constraints 10 and 11 are the conditions of completeness of binary variables in the model.

3.3 Model solution

For the supply chain network optimization in this research, we adapted the heuristic method based on Tabu Search proposed by Lee & Kwon (2010). These authors applied the heuristic for a supply chain considering plants, DCs and customers, but in this research we also added the raw material vendors. The proposed heuristic performs an iterative search of neighboring solutions, starting from an initial solution while checking the tabu list prevents returning to a recently visited solution, wherein at each iteration the neighborhood is generated by exchanging DCs and transport arcs, which are selected according to priority rules which represent an average unit cost for each operation. The heuristic step by step can be seen in Figure 1.

Lee & Kwon (2010) consider that the heuristics used decomposition networks to gain computational efficiency, while the meta-heuristics, such as tabu search, use priority rules for selection of facility and/or routes at each decision point. Thus, the network is decomposed into two sub-problems: decomposition of demand and supply decomposition, being applied in the first stage between DCs and customers, while the second regards the rest of the network.

In the demand decomposition, the DC and transport arcs are exchanged to form a neighbor solution with the use of a priority index and a tabu control mechanism. At this stage the DCs that will be opened and the plan for distribution of products from DCs to customers are determined.

For selection of the DCs and the arcs to be exchanged, Lee & Kwon (2010) suggest the use of a priority index, the *Unit Cost Ratio* (UCR). This index comprises the major costs and strongly influences the outcome of the objective function. Three types of indexes are suggested: the *UCR–F*, used in the generation of the initial solution; the *UCR–O*, in the DC change; and the *UCR–S*, used in the arc change.

3.3.1 Initial solution generation

For the initial solution generation, the DCs are selected based on a priority index, the *UCR–F*, which represents the cost of operating the DC per unit of product being obtained by the CD operation cost dividing the total capacity of the same. DCs with lower rates have aperture priority and customers with the highest demand are allocated to the lower rate DCs, while the capacity of CDs is not exceeded. The *UCR–F*$_w$ index of CD $w \in W$ is determined by 12:

$$UCR - F_w = \frac{CT_w^o}{CAP_w} \tag{12}$$

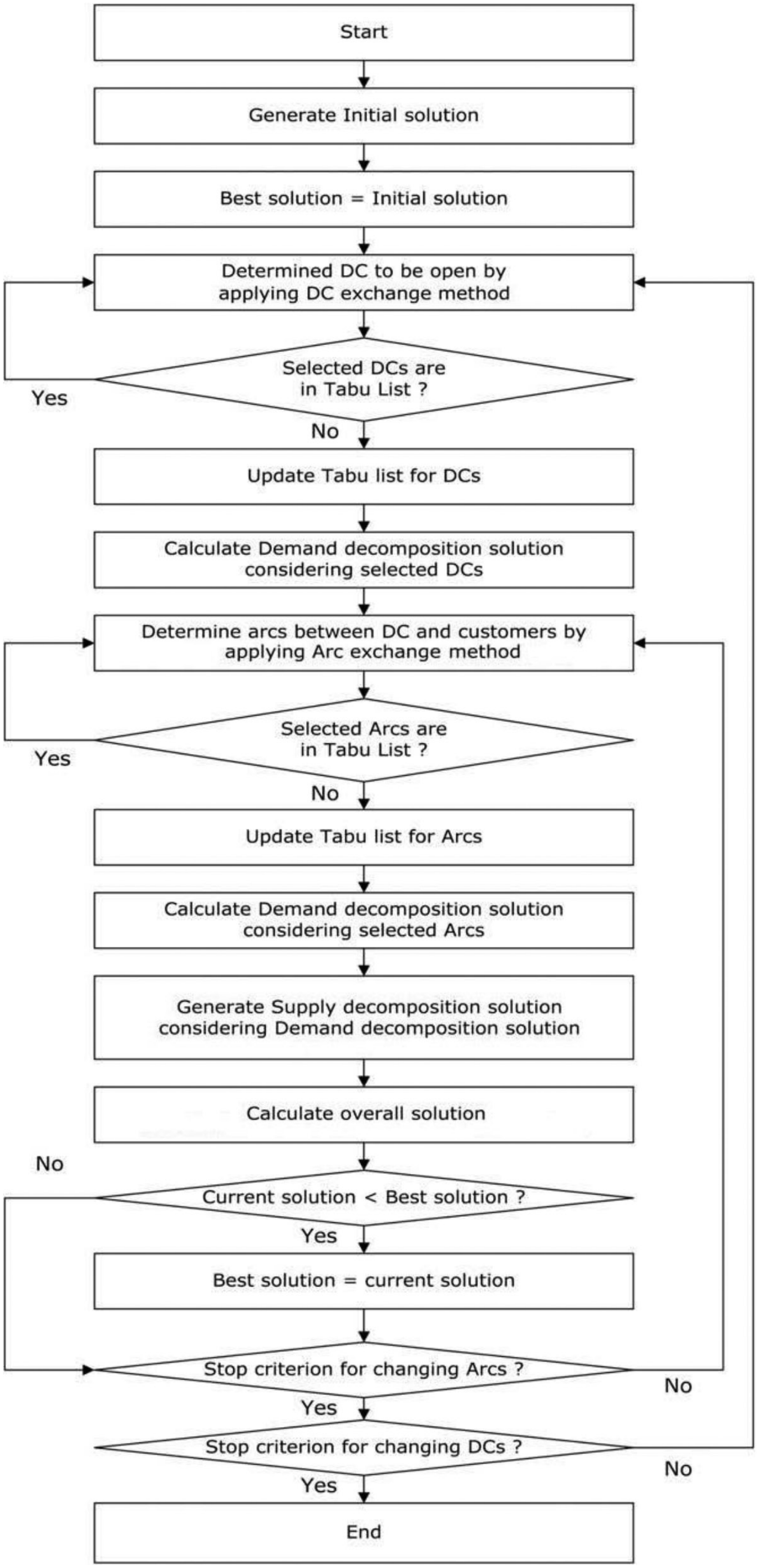

Figure 1. Overall procedure of heuristic. Source: adapted from Lee & Kwon (2010, p. 3097).

The procedure for generating the initial solution is presented in Chart 5.

3.3.2 Neighborhood generation: demand decomposition

In the neighborhood generation procedure during the demand breakdown, two methods are applied: DC exchange and arc exchange. The procedure for DC exchange is capable of generating new replacement surrounding the CD opened by closed, or vice versa. For this operation, it used the *UCR–O* index, which is the unit cost DC operation, defined by the sum of DC's operating cost, the cost of transportation between factories and the DC, and product shipping cost customers. DCs with lower values of UCR-O have opening preferably, and in the exchange procedure, the DCs with higher *UCR–O* indices are closed and replaced by closed DCs with lower rates. This can be seen in Chart 6.

In 13 is expressed the formula for determining the value of $UCR–O_w$ of CD $w \in W$.

$$UCR - O_w = \frac{\sum_f CT^t_{fws}}{NP_w} + \frac{\sum_c CT^t_{wcs}}{NC_w} + \frac{CT^o_w}{Q_w} \tag{13}$$

where:

Q_w = transportation amount passing through the DC $w \in W$;

NP_w = number of plants from which the products are transported to DC $w \in W$;

NC_w = number of customers served by DC $w \in W$;

Arc exchange method is used to generate neighborhood by replacing two arcs on the demand decomposition stage, seeking to reduce the cost of

Chart 5. Heuristic procedure of generating initial solution.

```
Step 1: Initialization and computation of the priority index
        Step 1.1: Set all distribution centers as closed;
        Step 1.2: Calculate $UCR–F_w$ for each DC;
        Step 1.3: Sort DCs in an increasing order according to calculated index;
Step 2: Demand decomposition solution:
        Step 2.1: Select DCs sequentially according to the sorted list in Step 1.3;
        Step 2.2: Allocate customers with higher demand to DCs with lower index, respecting the capacities of DCs;
        Step 2.3: If all demands are allocated to DCs, then stop.
        Else, then go to Step 2.1;
Step 3: Supply decomposition solution:
        Step 3.1: Generate supply decomposition solution and combine with the demand decomposition solution to
                  complete an initial solution.
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Fonte: adapted from Lee & Kwon (2010, p. 3097).

Chart 6. Heuristic procedure of Exchange DCs.

```
Step 1: Setting initial condition:
        Step 1.1: Classify DCs according to whether open or not;
Step 2: Calculation of $UCR–O_w$:
        Step 2.1: Calculate $UCR–O_w$ for each open DC;
        Step 2.2: Sort open DCs in a decreasing order of $UCR–O_w$;
Step 3: Distribution center exchange:
        Step 3.1: Select open DCs sequentially according to the sorted list;
            Step 3.1.1: Calculate $UCR–O_w$ for closed DCs according to transported quantity of selected
                        distribution center in Step 2.1;
            Step 3.1.2: Sort closed DCs in an increasing order of $UCR–O_w$;
            Step 3.1.3: Select closed DCs sequentially according to the sorted list and check feasibility by
                        comparing capacities of both selected open and close DC;
            Step 3.1.4: If it is feasible, then exchange DCs and stop procedure. Else, if there exist a closed DC
                        which has not been selected before, then go to Step 3.1.3;
        Step 3.2: If there exist an open DC which were not selected before, then go to Step 3.1 and repeat steps.
                  Else, stop procedure since DC exchange is not possible.
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Fonte: adapted from Lee & Kwon (2010, p. 3098).

Chart 7. Heuristic procedure of arcs exchange.

```
Step 1: Setting initial conditions:
        Step 1.1: Classify arcs according to whether used or not;
Step 2: Calculation of $UCR–S_{wc}$:
        Step 2.1: Calculate $UCR–S_{wc}$ for each used arc;
        Step 2.2: Sort used arc in decreasing order according to $UCR–S_{wc}$.
Step 3: Arc exchange:
        Step 3.1: Select used arcs sequentially according to sorted list:
            Step 3.1.1: Select another used arcs sequentially among remained used arc sets;
            Step 3.1.2: Assuming that selected two used arcs are exchanged, calculate $UCR–S_{wc}$ for each
                        exchanged arc;
            Step 3.1.3: Check feasibility by comparing capacities of DCs that are used by selected arcs; If it is
                        feasible, then go to Step 3.1.4. Else, go to Step 3.1.1 and repeat steps.
            Step 3.1.4: If the sum of $UCR–S_{wc}$ that is calculated in Step 3.1.2 is smaller than sum of $UCR–S_{wc}$ that
                        is calculated in Step 2, then exchange two arcs and stop procedure. Else, go to Step 3.1.1
                        and repeat steps.
        Step 3.2: If there are used arcs not selected before, then go to Step 3.1.3.
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Fonte: adapted from Lee & Kwon (2010, p. 3099).

shipping and handling of products for DC exchange that meets particular customer. Two arcs are selected randomly, and then calculates the $UCR–S_{wc}$ index for both. If the sum of the $UCR–S_{wc}$ after exchange arcs is smaller than before the change, the replacement of the arcs is performed. The $UCR–S_{wc}$ considers the sum of three terms: unit transportation cost, cost of CD $w \in W$ operation divided by the number of arcs utilized and the cost of handling products divided by the number of arcs utilized from the CD $w \in W$. The $UCR–S_{wc}$ index to the bow (w,c) is determined by 14:

$$UCR - S_{wc} CT^{t}_{wcs} + \frac{CT^{o}_{w}}{NC_{w} * QA_{wc}} + \frac{\sum_{s}\left(CT^{g}_{w} / NC_{w}\right)}{QA_{wc}} \tag{14}$$

where:

NC_w = number of customers served by the DC $w \in W$;

QA_{wc} = transportation quantity from the DC $w \in W$ to the customer c $\in C$.

Chart 7 presents the procedure for exchanging arcs.

3.3.3 Tabu procedure

To solve the problem we used three tabu lists, two for DC exchange procedure and the third for the arcs exchange procedure. At each iteration, an exchange of DCs and an exchange of arcs is carried out, and these are recorded in the tabu list. The search procedure is performed in a guided manner, i.e., each iteration is selected and the arc DC with lowest cost among those available for replacement.

For each CD exchange operation, two tabu lists are operated: one for the enclosed DCs and the other for open DC, that is, each time a CD is selected to be closed or opened in the local search, the corresponding list is checked to verify the possibility of the operation being carried out and, if the selected DC is already in the list, it must be given another CD to complete the operation. When changing the arcs, in turn, is newly registered, the pair of arcs and exchanged tabu list is used to inhibit the exchange of recently changed arcs, seeking to exploit new solution spaces.

Regarding the size of tabu lists, Lee & Kwon (2010) fixed it in 5 to CDs and 20 for the arcs, sizes that are appropriate and not varied widely during the trial. However, for this study, the size of the lists was determined individually for each instance, as the list size affects considerably the value of the objective function. Thus, several tests were performed to identify the list size to find the best outcome for each instance. Table 1 shows the size of the tabu list considered for solving each instance.

For Lee & Kwon (2010), Tabu Search is suitable for the proposed solution method, since the established priority rules tend to become concentrated in a single solution region, however, with the use of the tabu list, the exit of this region of local optimum is forced by exploring new areas in search of a better solution.

Lee & Kwon (2010) use two stopping criteria: 10 consecutive iterations without improvement and a maximum of 1,000 iterations. For this research, it was used as a stopping criterion 2,000 maximum iterations and 500 iterations followed without improvement.

After noticed the need for finished products in each DC, it was solved the supply decomposition subproblem. To determine which factory supplies each DC was used as a criterion the sum of transportation costs and production of products, while the DC chosen to present the lowest value of this combination.

For selecting vendors of raw materials, it was considered the cost of transport between supplier and factories. Knowing the need to produce in each factory, it is possible to calculate the need for feedstock production. Thus, the materials will be purchased from vendors that present lower transportation costs. The cost of the raw material was not considered because the values were very similar for all vendors, the most important transport cost for this step.

Table 1. Sizes of tabu lists.

Instance	DC	Arc	Instance	DC	Arc
1	5	9	12	7	20
2	6	18	13	7	50
3	7	25	14	7	100
4	8	26	15	8	25
5	9	50	16	8	50
6	5	9	17	8	120
7	5	25	18	9	24
8	5	40	19	9	44
9	6	20	20	9	150
10	6	50	21	6	20
11	6	110	22	6	100

Source: elaborated by the authors.

3.3.4 Instances solved

The heuristics developed was used to solve the 22 instances proposed by Farias & Borenstein (2012) and the results obtained were compared with the optimal solution found by the authors using CPLEX and the results of Lee & Kwon (2010).

The instances generated and presented in Table 2 have stressed the application of models in situations of different amounts of CDs, products, and customers; the number of providers, types of raw materials and factories were kept fixed in all instances, while the processing capacity and fixed costs of the CDs were established in order to present a realistic character to the problem addressed (Farias & Borenstein, 2012).

Besides the instances proposed by the authors, other four instances with real and complex features that solved to date in order to verify the efficiency

Table 2. Configuration of instances.

Instance	Vendors	Raw Materials	Factories	DCs	Group of Products	Customers
1	5	5	3	10	5	150
2	5	5	3	20	5	150
3	5	5	3	30	5	150
4	5	5	3	40	5	150
5	5	5	3	50	5	150
6	5	5	3	10	10	150
7	5	5	3	10	50	150
8	5	5	3	10	100	150
9	5	5	3	20	10	150
10	5	5	3	20	50	150
11	5	5	3	20	100	150
12	5	5	3	30	10	150
13	5	5	3	30	50	150
14	5	5	3	30	100	150
15	5	5	3	40	10	150
16	5	5	3	40	50	150
17	5	5	3	40	100	150
18	5	5	3	50	10	150
19	5	5	3	50	50	150
20	5	5	3	50	100	150
21	5	5	3	20	10	150
22	5	5	3	20	50	150

Source: adapted from Farias & Borenstein (2012).

of heuristic in a even more realistic scenario were generated and solved. The settings will be presented in the next chapter.

The heuristic has been developed in C ANSI programming language and the results were obtained on a computer with Pentium Dual-Core T4300 processor 2.10 GHz with 4 GB of RAM and Linux operating system version 3.0.0-12-generic Ubuntu 11:11.

Exposed the methodological procedures used to solve the problem of this research, in the next chapter we present and discuss the results.

4 Results and discussion

The initial solutions achieved in each instance and the final solution were analyzed, ie, the best solution identified during the heuristic process. It was observed that, on average, generated initial solutions could be improved to 3.87% with the application of the procedures of exchange of arcs and DCs. In the method proposed by Lee & Kwon (2010), the allocation of customers was to DCs performed at random, while this research, it was decided to allocate the greatest demands on DCs to present lower UCR, thus getting initial solutions already quite close to the best results.

Table 3 presents the solutions (in $) and the CPU time (in seconds) for each of the 22 instances, by comparing the results obtained with CPLEX and TS implemented in this study.

Making a comparison between the optimal and heuristic values for the 22 instances, it was found that the gap (difference between optimal solution and heuristic solution) changed by 0.18% (7 instance) to 7.74% (instance 13) taking a mean value of 4.98%. Lee et al. (2008) solved a problem with similar characteristics, using the CPLEX for optimization of a stage of the problem and a post-improved search method based on Tabu Search. The authors considered a network of factories, warehouses and CDs and, as a result, achieved an average gap of 7.94%, ranging between 3.05% and 13.57%. Whereas the average gap of this research was 4.98%, it is concluded that the method used herein was able to find results with 37.28% lower than those found by the previous authors.

It is important to note also, that of the 20 instances proposed by Lee et al. (2008), 10 considered 20 and 50 customers and could be resolved, while for the other 10 instances, containing 70 and 100 guests,

Table 3. Comparative of solution and CPU time obtained with CPLEX and TS.

Instance	Solution ($)			CPU Time (s)		
	CPLEX	TS	gap (%)	CPLEX	TS	Reduction (%)
1	16,970,300	17,796,420	4.87%	2.07	0.66	–68.12%
2	16,541,500	16,750,500	1.26%	2.42	0.25	–89.59%
3	17,484,800	18,605,000	6.41%	4.06	0.45	–88.87%
4	15,453,300	16,568,600	7.22%	7.65	0.16	–97.87%
5	15,051,100	15,857,900	5.36%	4.86	0.44	–90.86%
6	31,098,000	31,224,000	0.41%	2.45	0.53	–78.53%
7	30,755,440	30,811,316	0.18%	3.97	1.46	–63.17%
8	29,169,246	29,661,682	1.69%	9.61	5.63	–41.47%
9	28,816,500	30,275,000	5.06%	3.93	1.09	–72.26%
10	30,880,456	32,487,848	5.21%	10.97	2.16	–80.29%
11	31,226,678	33,249,280	6.48%	39.62	4.82	–87.84%
12	27,681,500	29,284,500	5.79%	4.39	1.95	–55.69%
13	29,728,252	32,029,352	7.74%	13.54	2.53	–81.32%
14	27,813,526	29,738,192	6.92%	36.44	3.42	–90.62%
15	28,525,950	29,899,900	4.82%	10.74	0.32	–97.00%
16	29,947,862	31,839,320	6.32%	15.03	2.71	–81.99%
17	28,943,138	29,780,336	2.89%	54.42	3.99	–92.67%
18	27,532,500	29,234,500	6.18%	4.96	0.56	–88.77%
19	27,763,300	29,810,824	7.37%	17.45	3.64	–79.13%
20	27,935,264	29,855,046	6.87%	38.47	4.82	–87.48%
21	60,940,660	63,570,312	4.32%	7.12	0.67	–90.60%
22	63,771,168	67,760,184	6.26%	13.23	2.84	–78.53%
Average			**4.98%**	**13.97**	**2.05**	**–81.03%**

Source: elaborated by the authors.

the authors did not managed to find results because the maximum computational time given 300 seconds has been reached.

Lee & Kwon (2010) results have been achieved with an average gap of only 3.53% for all instances resolved, 29.12% lower than the value obtained in this study. It should be noted that instances of greater complexity addressed by the authors considered only 20 DCs, 80 guests and 5 products, while this study addressed scenarios with 50 DCs, 150 clients and 100 products, and include the provision of raw materials, disregarded the problem the authors. Another reason worth mentioning refers to the fact that Lee & Kwon (2010) have used the CPLEX for solving the decomposition problem of supplies, thus getting great results at this stage. In this research it was decided not to use the CPLEX, aiming to build a fully independent heuristic market code, which can be more useful to organizational practice.

About the computational time required to obtain the optimum results for CPLEX and the heuristics as well as the percentage of reduction of the execution time comparing these approaches, it was observed that the heuristic was able to solve instances in relatively short time periods, whereas the average percentage reduction of run time was 81.03%. The execution times obtained in this study ranged from 0.16 (instance 4) and 5.63 seconds (Instance 8), with an average of 2.05 seconds, the CPLEX was able to solve instances averaging 13.97 seconds time ranging from 2.07 to 54.42 seconds as can be seen in Table 3.

Lee & Kwon (2010) had a heuristic variation in execution time ranging from 0.55 to 260.50 seconds, with an average time of 42.75 seconds value higher than 95.20% obtained here. This significant difference between the running times obtained in this study and the Lee & Kwon (2010) may be justified due to the use of random elements in the generation of initial solution of the authors, which forced them to repeat 10 times the heuristic for each instance looking for a better result, penalizing the total execution time.

Lee et al. (2008) determined as one of the stopping criteria 300 seconds of running, with 10 out of the 20 instances could not be solved within that time limit. In the case of the heuristic in this study, the maximum running time of an instance was only 5.63 seconds, which proves the efficiency of the proposed method and the computational time, which is a crucial element of choice between two heuristic techniques, according to Bräysy & Gendreau (2005).

4.1 Real instances

After examining the performance of the heuristic for instances from Farias & Borenstein (2012), it was proposed other four instances containing real features, since the amount of data involved and scenarios in these problems are greater. Thus, the aim was to check the efficiency of the proposed heuristic solving the problems of these dimensions, as the CPLEX was not able to get results for instances with these characteristics. Table 4 shows the configuration of the instances with real characteristics resolved.

Instances A, B and C consider a real supply chain network, and the costs were generated randomly, and the D instance, which considers the possibility of opening 100 DCs that meet the demand of 1,000 customers by 130 different products is designed to check the heuristic behavior in an even larger scenario. It is noteworthy that in the investigated literature there are no studies that have addressed a network with similar characteristics to that instance.

Comparing the initial and final solutions to the scenarios with actual characteristics, we note the improvement percentage between solutions ranged from zero to 7.13%, averaging 3.42% improvement. The average percentage of improvement is consistent with the value identified in the instances previously explored, where the difference between solutions was 3.58%.

About the runtime instances with real characteristics solved, it was observed that this ranged from 6.52 seconds to the B instance and 117.91 seconds for the D instance, and the instance A, solved in 6.97 seconds, and the C in 35.68 seconds.

The resolution of the four instances with real characteristics allows proving the proposed heuristic efficiency to solve optimization of complex problems of real supply chain networks and can be used by

Table 4. Configuration of the instances with real characteristics.

Instance	Vendors	Raw Materials	Factories	DCs	Group of Products	Customers
A	5	5	2	10	132	261
B	5	5	2	20	132	261
C	5	5	5	40	130	200
D	5	5	5	100	130	1000

Source: elaborated by the authors.

managers in decision-making, both at the strategic level (determining the CDs to be opened), as the operational level (determining the amount of product to be transferred from one site to a CD).

5 Conclusion

Although there are several models for optimization of supply chain networks, the real problems become too complex to be solved, as large bodies require a large computational time running and often can not find solutions. Given the importance of reducing logistics costs through supply chain optimization and complexity of problems with real bodies, the aim of this study was to implement and evaluate a heuristic based on Tabu Search to optimize a supply chain network.

To achieve this goal, the method proposed by Lee & Kwon (2010) was adapted and implemented, as presented in the methodological study procedures. Main changes in the method of the authors, like the option not to work with randomness in the generation of initial solution and the addition of raw material vendors to the issue were implemented. Once implemented the heuristic, problem was solved considering 22 instances proposed by Farias & Borenstein (2012), which enabled the comparison and evaluation of the results found by the heuristic with the optimal values.

By analyzing the results it was concluded that the heuristic found solutions implemented with cost 4.98% more than the optimum values, while Lee & Kwon (2010) obtained results only 3.53% higher, but in different instances. The difference in results may be related to the fact the instances addressed here are more complex, since in smaller bodies such as the scenario 2, for example, the results obtained in this study were better than those of Lee & Kwon (2010) and it was possible to find solutions with a gap of only 0.76% against 4.77% of authors with a time of 2.54 seconds vs. 17.35 seconds.

It was also found that the heuristic method used to solve the problem was able to find results with an average time of 2.05 second, relatively small value compared to the average time Lee & Kwon (2010), which was 42,75 seconds for less complex instances. This substantial reduction in execution time is due to the improvement in the generation of initial solution proposed in this research. While Lee & Kwon (2010) opted for allocating customers randomly DCs, this research sought to allocate greater demands to lower-cost DCs, generating a better and fixed value initial solution. Using randomness in the initial solution, the authors needed to repeat 10 times each instance for better results, while for this research, the results were found with only a single repetition.

The way a final solution approaches the optimum result is a standard quality measure, therefore we can conclude that the heuristic implemented in this study meets this requirement, since in a very small solution time is capable of finding good solutions with values, on average, 4.98% above the optimal result.

The problem was also solved for four instances with actual characteristics, in order to verify the performance of the method in real problems. The heuristic was able to resolve the four instances in reduced computational times, ranging from 6.52 seconds to a network with 2 factories, 20 CDs, 132 products and 261 clients to 117.914 seconds to 5 plants, 100 CDs, 130 products and 1,000 customers.

Thus, we conclude that the presented heuristic optimization is efficient for networks with complex supply chains, being able to get acceptable results on a computer running long enough optimized.

As a limitation of this study, it appears that the implemented heuristics are able to solve only the single-source approached model, and for use in approaches that do not consider this restriction (usual in several real supply chains), it would need adjustments.

Finally, some topics may be raised as suggestions for future research, namely the possibility of multimodal transport including (train, truck, ship, plane, etc.) between the actors of the network, since this is the reality of part of the supply chain and can even closer to the model of reality. Another issue that could be investigated is the t index (time) to the model, as several supply chains have the constraint of deadlines, which should be respected. An approach that does not consider the single-source restriction can also be explored in future research and the development of other heuristic approaches to solving this problem, giving bases for a comparison between two heuristics to choose the method that best applies to this problem.

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