

# The In-house Logistics Routing Problem

Marcelus Fabri<sup>a,\*</sup> and Helena Ramalhinho<sup>b</sup>

<sup>a</sup>*Department of Information and Communication Technologies, Universitat Pompeu Fabra, C/ Roc Boronat, 138, Barcelona, 08018, SPAIN.*

<sup>b</sup>*Department of Economics and Business, Universitat Pompeu Fabra C/Trias Fargas, 25-27,08005, Barcelona, SPAIN  
E-mail: 1st.marcelusfl@gmail.com [F. Author]; 2nd.helena.ramalhinho@upf.edu [S. Author]*

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## Abstract

In this work, we consider the internal logistics processes in the car assembling company SEAT S.A. We focus on the design of the supplying routes from the warehouse towards the workstations along a production line. The In-house Logistics Routing Problem (ILRP) can be seen as an extension of the classical Vehicle Routing Problem considering special features such as long-term fixed routes, unknown orders, backorders, and homogeneous fleet. To solve the ILRP, we propose an Integer Linear Programming (ILP) model and a Simulation Iterated Local Search (SimILS) algorithm. We conduct two computational experiments. The first experiment analyzes the methods' performance, and the second one compares the SimILS results with the current company's routes, considering real data provided by the SEAT S.A. The results show that the SimILS provides the best overall results overcoming both the ILP approach and the current company's solution, leading to a significant improvement in the company's processes.

*Keywords:* Metaheuristics; Integer Programming; Logistics; Combinatorial Optimization; Automotive Industry

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## 1. Introduction

Designing efficient logistics systems has been one of the main topics in many business, including manufacturing ones. The logistics field is related to the flows of materials between and within organizations. Indeed, companies focus more and more on the logistics field. The logistics area is seen as a strategic field to gain competitiveness in markets by reducing costs as well as providing a better service's level to customers, see Muñuzuri et al. (2005). Also, it is a relevant field considering the industry 4.0's applications.

This work focus on internal logistics operations, which means flows of materials inside the same business or the same plant, for example, from a warehouse (WHS) to an assembly line. The improvement of these flows can lead to a reduction of the delays, production's disruptions, and also contribute to minimizing logistics costs. Precisely, this work considers the automotive sector to conduct its research over an actual internal logistics system.

\* Author to whom all correspondence should be addressed (e-mail: marcelusfl@gmail.com).

We highlight that this work was carried out under collaboration and agreement with SEAT S.A., which provided us with all the necessary data and support. SEAT (Sociedad Española de Automóviles de Turismo) is a Spanish company, a subsidiary of the Volkswagen Group ([www.seat.es](http://www.seat.es)). In 2019, SEAT was present in more than 75 countries. Also, the company has manufactured more than 500,000 vehicles in 2019.

### 1.1. The In-House Logistics Routing Problem

To provide suitable guidance to the reader, we present the essential pillars that define the main SEAT’s internal logistics processes or the in-house ones. In other words, these processes refer to the materials handling inside the company. Consequently, the in-house activities are in charge of storing the received materials in the warehouse, executing the picking of these materials, and proceeding with the supply of the placed orders in the assembling lines. For materials-handling related works see Mason et al. (2003); Poon et al. (2009); Klug (2013); Atieh et al. (2016); Zhou and Peng (2017); Ribino et al. (2018).

Then, those placed orders are supplied through routes or logistics flows. The supplying routes are the logistics flows responsible for delivering those materials whose consumption rate is not regular. A non-regular consumption rate may occur due to products’ customization issues or a not standardized placing orders process, for example. The main processes of the supplying routes are presented in Table 1.

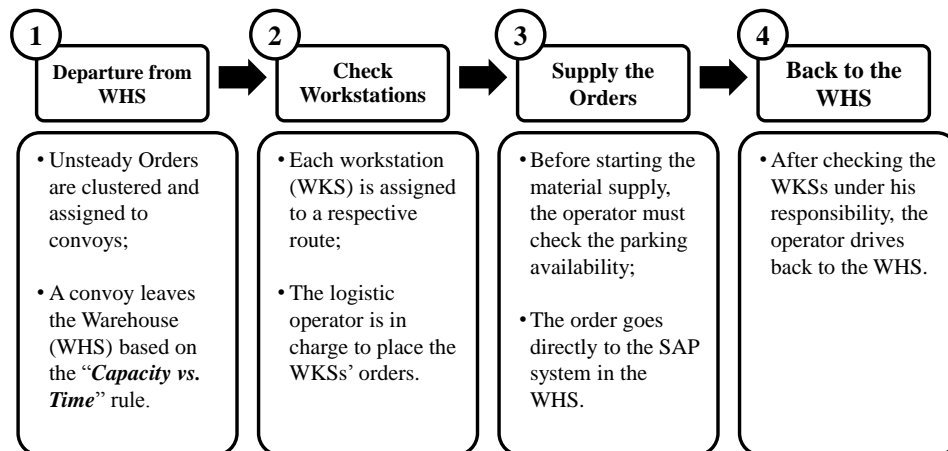


Fig. 1. The summary of the processes of a non-regular departure logistic flow.

First, the warehouse (WHS) receives orders through the commercial system SAP. Notice that these orders are not steady, which results in a non-regular departure. Consequently, a "Capacity vs. Time" rule is defined. This rule ensures that each convoy leaves the WHS as soon as it is either loaded completely or a defined amount of time is achieved since the first order had been assigned to that convoy. So, there are two criteria that regulate the departure that refer to the capacity and the time. So, after the arrival of the first orders, the maximum time a convoy can wait to be loaded is 60 minutes in this work. Moreover,

there is a relevant materials' classification that concerns to the Stocking Keeping Unit's (SKU) size. In the company, there are two main classes of SKU, i.e., the Small Boxes class (SB) and the Large Container (LC) one. So, there is a premise that establishes the division between SB convoys and LC ones. In other words, it is not allowed to mix both SB and LC in the same convoy. Note that an order is viewed as the request of a single SKU in this work.

Afterward, the second phase is the checking workstations one. In SEAT, workstations are clustered into logistics groups and many of them can be created. As a result, a logistics group corresponds to a subsection of the assembling line compound of a set of workstations. Usually, a logistic group's workstations are close to each other. Besides that, the company assigns one operator to one route. Also, it is assigned a set of logistics groups to each router. Each logistics group is exclusively linked to a router. As a result, a logistics group, or a set of workstations, is not allowed to be attended by different routes. That premise is valid for routes of the same SKU class only. Other relevant premises refer to the logistics flows' trajectory. By definition, a logistics flow must complete all its trajectory whenever it starts. Also, the set logistics flows are considered to be kept fixed for a long-term period, e.g., months. It is justified because the logistics operators are in charge of both supply the material and place the orders. We define this procedure as *self-ask-supply procedure*. As a result, the routes are fixed to keep the supplying activities under control as well as the placing orders activity.

Figure 2 illustrates the amount of orders placed over 117 days. That data correspond to two workstations' orders. Notice that the orders present an unsteady behaviour. In this work, the orders data is gathered through the company's SAP system. As a result, real-historical data was approached.

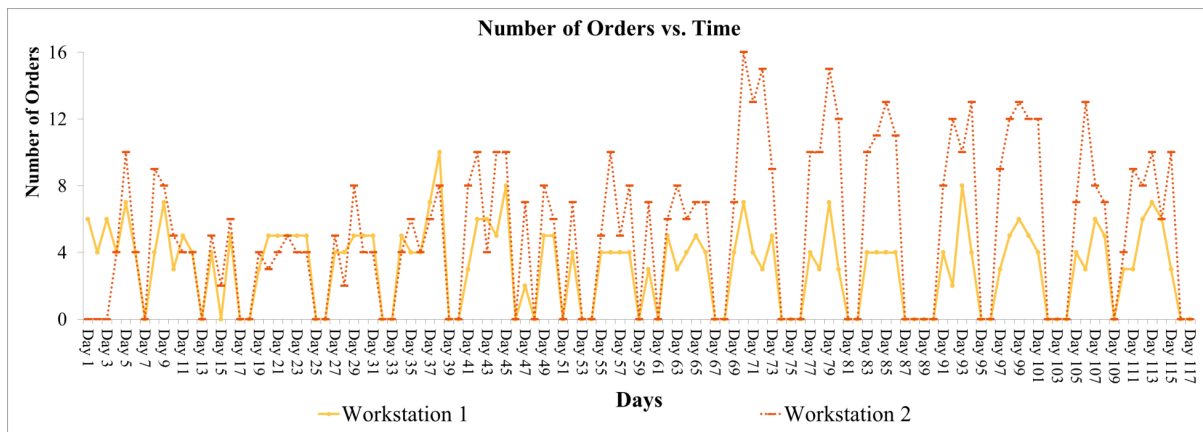


Fig. 2. An example of two workstations requests' pattern over three months.

Later, the third phase refers to the supplying activity. During a route trajectory, an operator must park the convoy to supply a workstation. Then, the operator supplies the material and restart its trajectory. Note that the operators spend time to place the SKU in the right position.

Lastly, the final step is the return to the WHS. After checking the workstations' under his/her responsibility, the operator returns back to the WHS to deliver the empty racks and get new loaded ones. Later, the convoy departs from the WHS towards the assembly line, and the cycle starts again. Therefore, note that the definition of the logistics flows in SEAT is a challenging task. Furthermore, it becomes even

more inspiring when fixed routes scenario is considered along unsteady orders behaviors. For further references of routing strategy, see Mehami et al. (2018); Vavřík et al. (2017); Lima and Ramalhinho (2017).

Concerning to the assembling workshop, it is composed of more than 120 workstations. Those workstations are able to produce nearly 2,400 personalized cars each day. As a result, the logistics manager must define the most suitable set of fixed routes to supply all the required materials throughout the day from the warehouse to the production line. For production-flow related works, see Patchong et al. (2003); Faget et al. (2005); Michalos et al. (2010); Seebacher et al. (2015).

As mentioned, the placed orders are sent to the SAP system. Later, an outsourced company organizes all the orders and execute the picking activities in the warehouse according to the First-In-First-Out (FIFO) criterion. Figure 3 illustrates the company’s workshop layout. For layout-evaluation related works, see Martínez-Barberá and Herrero-Pérez (2010); Horta et al. (2016).

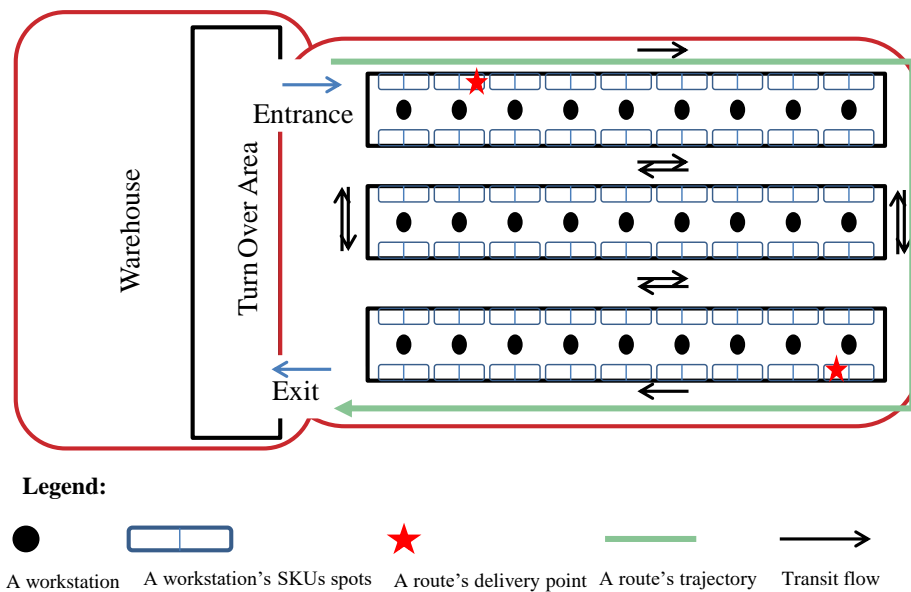


Fig. 3. An illustration of the company’s workshop, which is composed of a warehouse, a turnover area, and an assembly line distribution.

To sum up, the Internal Logistics Routes Management (ILRM) system applied by SEAT is summarized as follows: (i) long-term and fixed routes; (ii) self-ask-supply procedure; (iii) First-In-First-Out criterion; (iv) each workstation is assigned to one logistics operator only; (v) convoys are loaded with one type of product only, which are LC or SB; and (vi) unsteady demand. Moreover, the logistics director’s main goal is to design an ILRM system that provides a set of routes that incurs in smaller costs as possible. The costs are measured in the sense of the number of routes, the distance covered by these routes, and the number of delayed delivery or backorders. Among these three metrics, the number of routes is the most important criterion for the company.

Those premises may place the company’s designing routes tasks in the Vehicle Routing Problem

(VRP) class of problems. Next, we present the related classes of VRP that more similarities share with the company's premises.

### 1.2. Related Work

According to Laporte (2009), the VRP is stated as the problem of designing least-cost delivery routes from a depot to a set of geographically sparse customers, subject to side constraints. Consequently, due to a significant variety of side constraints, as well as different optimization goals, there are several variants of the problem because of the diversity of operating rules and constraints found in real-life applications. To further explanation about the VRP methodology, see Toth and Vigo (2002). Also, for a complete survey of the VRP literature, see Laporte et al. (2000); Laporte (2009); Braekers et al. (2016); Koç et al. (2016).

Notice that the amount of works that compound the VRP area is considerable. So, from now on, only the VRP classes that are similar to the work's approach will be discussed. These classes are presented by Table 1, which resumes the main related work considering the routes' properties aspects, as well as the placing orders aspects.

Table 1

The summary of the VRP classes structure, regarding the differences between the evaluated In-house Routing Problem (ILRP) and the related VRP found in the literature. The related VRP classes are the following: Traditional VRP (TVRP), Consistent VRP (CVRP), Periodic VRP (PVRP), Stochastic VRP (SVRP), Dynamic VRP (DVRP), and Inventory Routing Problem (IRP).

ID	Characteristic	ILRP	TVRP	CVRP	PVRP	SVRP	DVRP	IRP
1	Self-ask-supply order approach	x						
2	Automatic/Forecasted orders approach		x		x	x	x	x
3	Deterministic demand		x	x	x			x
4	Stochastic and/or unknown demand	x				x		x
5	Fixed routes during the time horizon	x		x				
6	Variable routes during the time horizon					x	x	x
7	Node permanently linked to a router	x		x				

According to the surveys presented by Laporte (2009) and Braekers et al. (2016), the traditional VRP's primary objective is to minimize the total cost of routing a fleet of vehicles to supply a set of clients. Among the traditional VRP is the Asymmetric Capacitated VRP (ACVRP), which is defined by a asymmetric distance matrix and capacitated fleet, Crainic and Laporte (2012). Likewise, the major objective of the ILRP is to minimize the total cost of routing a fleet of vehicles to supply a set of clients. Also, the ILRP aims to minimize the total number of vehicles, the routes' distance and the number of backorders.

Regarding the Consistent VRP, the problem was introduced by Groër et al. (2009). In this scenario, the routes are kept fixed, and the drivers with the routes as well. Orders are known in advance by the managers. Also, when a customer receives service, the same driver visits the client at roughly the same time over the planning horizon. In the ILRP, the routes must be kept fixed on the long-term horizon as well. On the contrary, the router is the one in charge of placing orders instead of the client (self-ask-supply procedure), which contributes to making the demand stochastic.

Concerning the Stochastic VRP, it arises whenever any part of the data is stochastic or unknown in advance such as stochastic travel times or stochastic demand, see Gendreau et al. (1996); Adulyasak and Jaillet (2016). The main idea of the Stochastic VRP is to compute a set of routes that perform well considering the stochastic data input. In this work, the input data that is considered as stochastic one is the demand. The demand is viewed as stochastic and unknown due to the following factors: (i) self-ask-supply procedure; (ii) issues in the assembly line, and (iii) flexible cars-production scheduling, which is not shared among the departments. The stochastic demand behavior approach can also be observed in Bertsimas (1992); Novoa and Storer (2009).

The Dynamic VRP is described by Braekers et al. (2016), in which relevant data is continuously updated over the considered time horizon, such as the costumers' demand. Then, based on these inputs, the vehicles could adapt their routes dynamically. By contrast, the ILRP does not allow routes adaptations. A practical example of the Dynamic VRP is the taxi fleet management. Also, Albareda-Sambola et al. (2014) consider probabilistic information to compute each period's set of routes.

Regarding the Periodic VRP application, it assumes that the customers require visits on one or more days within a planning period. Also, there are a set of feasible visit options for each customer. A VRP is solved for each component in the planning period. Usually, the main goal is to minimize the total distance traveled over the planning period. Francis et al. (2007) define the operational complexity in implementing a solution to the periodic VRP, such as crew size definitions.

Lastly, Coelho et al. (2014) and Moin and Salhi (2007) present a literature review of the Inventory-Routing Problem (IRP), in which the demand is stochastic, and there are not clients' orders. Instead, the supplier decides when to visit each customer, based on forecasts, communications, and monitoring. Note that deterministic demand is also possible. The planning horizon is multiple periods in length. Note that the IRP and the VRP are different categories of problems. However, they share some concepts, such as the routing calculations and pursuing solutions with a minimal number of routes.

Regarding the VRP tackled by this work, it is defined as **In-house Logistics Routing Problem (ILRP)**. It is a VRP and, consequently, a NP problem as stated by Dantzig and Ramser (1959). Also, to the best of the authors' knowledge, it represents a novel VRP approach. The In-house Logistics Routing Problem is summarized as follows: (i) stochastic and unknown demand; (ii) self-ask-supply approach; (iii) long-term and fixed routes; (iv) drivers must return to the depot after concluding the route; (v) orders are made throughout the time-horizon; (vi) backorders are allowed; (vii) each customer is assigned to a route; (viii) fixed-customer-sequence definition; (ix) capacitated; and (x) homogeneous fleet. Those characteristics are observed in many problems presented in the literature. However, those aspects are not viewed all together to compound a similar VRP approach.

The motivation of this work is to provide the company with a set of Operational Research methods to support the routing-related processes. As a result, three major objectives are faced in this work. Firstly, propose a deterministic mathematical model based on Integer Linear Programming (ILP), which provides solutions to the described problem. Secondly, present a simulation-based Iterated Local Search (SimILS) metaheuristic capable of calculating good solutions for large-scale and stochastic versions of the cited problem. Finally, apply these methods to a real data context and analyze the results.

Consequently, three major objectives are pursued that are translated into the following primary Key Performance Indicators (KPIs): (i) the number of routes; (ii) the total routes' distances; and (iii) the total volume of materials not supplied on time (backorders). All of these indicators are standardized under the same measure, a cost function defined by the company.

The paper is organized as follows. Section 2 and 3 describe the Integer Linear Programming (ILP) formulation and the SimILS, respectively. Next, Section 4 presents the experiments and reports the computation results. Finally, Section 5 concludes the paper.

## 2. Mathematical Formulation

The Integer Linear Programming (ILP) model of the deterministic version of the In-house Logistics Routing Problem (ILRP) is an extension of the Asymmetric Capacitated VRP model described in Crainic and Laporte (2012). The main objective of the mathematical model is to find the optimal-fixed routes to be applied. Therefore, an important aspect of the model is the input data, in particular, how the workstations' orders are considered in the model.

As mentioned in section 1, the workstations' orders are gathered through the SEAT's SAP system. Consequently, the orders are a sample of historical data. Then, the total demand of a workstation will be the sum of the orders clustered chronologically over specific time windows or periods. See figure 4 for further information about orders clustering. As a result, we are introducing a sample of historical and known data that is collected from stochastic processes. The details of the ILP model are detailed next.

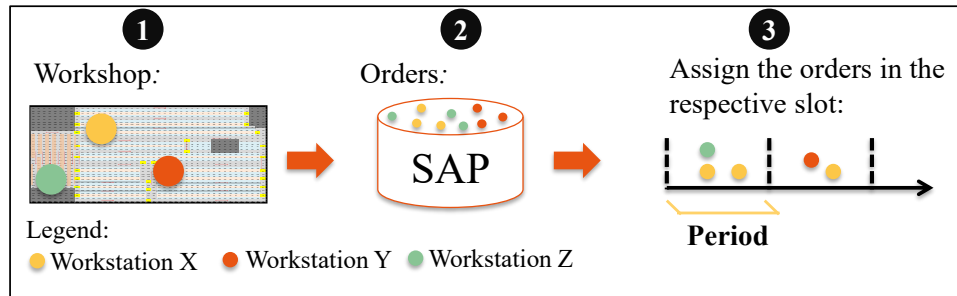


Fig. 4. Steps to Cluster orders into periods: (1) to select the workstations in the workshop; (2) to collect the respective orders in the Orders' system; (3) to place them in the time-horizon chronologically. Later, those orders may be clustered considering the time-window assigned to a period.

The deterministic version of the ILRP's notation:

- $(n \in N)$  the set of workstations to supply, in which  $(n = 1)$  represents the depot
- $(a \in A)$  the arc set
- $(l \in L)$  the periods set, in which  $L$  represents the complete time horizon
- $(r \in R)$  the routes' frequency set
- $C$  the convoy's capacity
- $MC$  the fixed travel cost spent to go from node  $(i \in N)$  up to node  $(j \in N)$
- $RC$  the fixed cost of introducing a route
- $SC$  the fixed cost of a backorder
- $SC$  the distance between nodes  $(i, j \in N)$  is  $(d_{ij})$
- $K$  the maximum number of convoys
- $T$  one period's length

- $tsup$  the time required to supply a material at the delivery point  
 $v$  the convoy's average speed  
 $R$  the maximum frequency (laps) a route can have within one period  
 $d_{il}$  the demand of the node ( $i \in N$ ) at the period ( $l \in L$ ), which is the demand of a workstation during a considered period  $l$   
 $x_{ijk_r}$  This variable will be equal 1 if arc  $(i, j) \in A$  belongs to the route ( $k \in K$ ) and has a frequency ( $r \in R$ ) within a period, 0 otherwise  
 $y_{ikr}$  This variable will be equal 1 if node ( $i \in A$ ) is visited by vehicle ( $k \in K$ ), which has a frequency ( $r \in R$ )  
 $bc_{lk}$  This variable represents the backorders inserted in the vehicle ( $k \in K$ ) at the period ( $l \in L$ )  
 $f_{kr}$  This variable represents the frequency ( $r \in R$ ) that a route ( $k \in K$ ) has within each period ( $l \in L$ )  
 $add_k$  This variable defines the additional capacity that a route ( $k \in K$ ) can receive

Notice that deterministic data values, such as speed and a material's supplying time were defined by the company; and the considered workstations' orders were based on historical data. The ILP model is presented next:

$$\min \sum_i^N \sum_{j \setminus (i \neq j)}^N MC d_{ij} \sum_k^K \sum_r^R x_{ijk_r} + \sum_k^K \sum_{j \setminus (j \neq 1)}^N \sum_r^R RC x_{1jkr} + \sum_l^L \sum_k^K SC bc_{lk} \quad (1)$$

$$\sum_r^R f_{kr} \leq 1 \quad \forall k \in K \quad (2)$$

$$\sum_{i \setminus i > 1}^N y_{ikr} \leq f_{kr} |N| \quad \forall k \in K, r \in R \quad (3)$$

$$\sum_k^K \sum_r^R y_{ikr} = 1 \quad \forall i \in N \setminus i > 1 \quad (4)$$

$$\sum_k^K \sum_r^R y_{1kr} \leq K \quad (5)$$

$$\sum_r^R \sum_{i \setminus i > 1}^N (D_{il} y_{ikr}) + bc_{(l-1)k} \leq \sum_r^R (rC f_{kr}) + add_k + bc_{lk} \quad \forall l \in L, k \in K \quad (6)$$



$$\sum_{j \setminus (j \neq i)}^N x_{ijk_r} = y_{ikr} \quad \forall k \in K, r \in R, i \in N \setminus i \neq 1 \quad (7)$$

$$\sum_{j \setminus (j \neq i)}^N x_{jik_r} = y_{ikr} \quad \forall k \in K, r \in R, i \in N \setminus i \neq 1 \quad (8)$$

$$\sum_{i, j \in S \setminus (j \neq i)}^N x_{ijk_r} = |S| - 1 \quad \forall S \subset N, k \in k, r \in R \quad (9)$$

$$add_k \leq C \quad \forall k \in K \quad (10)$$

$$\left( \sum_r^R \sum_{j \setminus (i \neq 1)}^N (D_{il} y_{ikr}) + bc_{(l-1)k} - bc_{lk} \right) t_{sup} + \quad (11)$$

$$\sum_r^R \sum_i^N \sum_{j \setminus (i \neq j)}^N r * (d_{ij}/v) x_{ijk_r} \leq T \quad \forall k \in K, l \in L$$

$$[T - (r + 1) \left( \sum_i^N \sum_{j \setminus (i \neq j)}^N (d_{ij}/v) x_{ijk_r} \right) - (f_{kr} r C t_{sup})] / t_{sup} \leq add_k \quad \forall k \in K, r \in R \quad (12)$$

$$x_{ijk_r} \in \{0, 1\} \quad \forall i, j \in A, k \in K, r \in R \quad (13)$$

$$y_{ikr} \in \{0, 1\} \quad \forall i \in N, k \in K, r \in R \quad (14)$$

$$f_{kr} \in \{0, 1\} \quad \forall k \in K, r \in R \quad (15)$$

$$bc_{lk} \in Z^+ \quad \forall l \in L, k \in K \quad (16)$$

$$add_k \in Z^+ \quad \forall k \in K \quad (17)$$

The objective function (OF) (1) minimizes the sum of the costs related to the total distances covered by all the routes, the number of routes, and the costs related to the backorders of the route ( $k \in K$ ) at a period ( $l \in L$ ). The constraints (2) define the number of laps, or the frequency ( $r \in R$ ), that route ( $k \in K$ ) does during one period. Constraints (3) state the maximum number of nodes a route ( $k \in K$ ) can visit, considering its frequency ( $r \in R$ ). Constraints (4) state that each customer must be attended by only one route. Constraint (5) states that the depot must be visited by  $|K|$  vehicles at most. Next, the constraints (6) define the number of backorder  $bc_{lk}$  of the route ( $k \in K$ ) in the period ( $l \in L$ ). The constraints (7) and (8) define that the vehicles that visit a node ( $i \in N$ ) must depart from that location after the supplying activity. The constraints (9) are responsible for avoiding the sub-tours to happen. The constraints (10) state that the maximum additional capacity a route can receive is fewer or equal to  $C$ . The constraints (11) state that each route can last up to  $T$  minutes, taking into account the capacity, the supplying time, the distance, and the traveling speed. The constraints (12) define the maximum additional capacity a route can receive, based on the amount of time left in a period. Lastly, constraints (13), (14), (15), and (17) define the domain of the variables.

Notice that the constraints (6), (10), and (12) aim to increase a convoy's capacity as much as possible. To do so, the constraints consider a rule called as **residual capacity**, which is explained as follows. A convoy's capacity is calculated through a function that has the following parameters: (i) convoy speed; (ii) period duration; (iii) time to supplied materials; and (iv) route's length. For example, suppose one scenario, in which a period has 60 minutes and a route's duration is about 21 minutes, including the supplying time to place all materials in the correct place. Consequently, the route can complete two trips within 60 minutes. If the convoy has its capacity limited to 4 orders per travel, the capacity will be equal to 8 as a result. Nevertheless, there are 19 minutes left to supply. So, we add to the capacity the exact number of orders the convoy is able to supply and back to the depot before finishing the current period. So, if the trajectory takes 12 minutes, the supplying procedure three minutes per order and there are 19 minutes left, the algorithm will be able to add two units more in the total capacity. As a result, the total capacity of this route will be ten units per period. That procedure enables the algorithm to come closer to real practice.

To obtain the solutions for this model, the AMPL language was used and solved by CPLEX 12.8.0, as we explain in section 4.

Also, note that the model evaluates the workstations' order for each period to compute the optimal set of fixed routes. Besides that, the model calculates the routes taking into account every single workstation as one independent node. As a result, the model does not consider the company's logistics group concept, but a more detailed one.

### 3. Simulation-based Iterated Local Search Metaheuristic

According to Glover et al. (1996), heuristics may be linked with other approaches such as simulation procedures. Following this premise, we have implemented an Iterated Local Search (ILS) metaheuristic, in which a simulation procedure is embedded. For ILS metaheuristic related works, see Vansteenwegen et al. (2009); Penna et al. (2013); Coelho et al. (2016); Lourenço et al. (2019).

This aggregation is defined as Simulation-based Iterated Local Search (SimILS) metaheuristic that was proposed by Grasas et al. (2016). According to the authors, the junction of a standard ILS metaheuristic framework and a simulation-optimization procedure result in a method capable of dealing with stochastic COPs, such as real problems whose demand is unknown.

In this work, the simulation is useful to deal with the workstations' orders that present a stochastic behavior. Consequently, we can take advantage of this method to simulate the number of backorders of each 60-minute period, see Figure 4. To execute the simulation, we take into account a defined set of routes as well as the company's parameters. We highlight that both ILP and SimILS methods share the same objective function, which is defined by expression 1 presented in Section 2.

Remember that we have to assign costs, or weights, to each component of the objective function. Besides, the main managerial goal of the company is to minimize the number of routes. Consequently, the weight assigned to the number-of-routes factor will be always higher than the other two components. Next, the SimILS algorithm is presented.

The ILS metaheuristic implementation is composed of four main steps, which are defined as follows: (i) compute an initial solution; (ii) execute a Local Search, which improves the solution initially obtained; (iii) execute the perturbation phase, where a new starting point is computed through a perturbation of the

solution returned by the Local Search; (iv) acceptance Criterion, which decides from which solution the search should continue. Concerning the simulation embedded in the ILS procedure. It is responsible for calculating the objective function of the problem. Algorithm 1 presents the SimILS framework.

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**Algorithm 1** The SimILS Algorithm

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1:  $(S_0) \leftarrow$  Generate_Initial_Solution
2:  $(S^*) \leftarrow$  Execute a Local_Search( $S_0$ )
3:  $(S^*, of(S^*)) \leftarrow$  Simulation( $S^*$ )
4: while Stopping criterion is not met do
5:    $(S') \leftarrow$  Perturbation( $S_*$ )
6:    $(S^{**}) \leftarrow$  Execute a Local_Search( $S'$ )
7:    $(S^{**}, of(S^{**})) \leftarrow$  Simulation( $S^{**}$ )
8:    $(S^*) \leftarrow$  Acceptance_criterion ( $S^{**}, S^*$ )
9: end while
10:  $(S^*, of(S^*)) =$  Simulation( $S^*$ )
11: Return ( $S^*, of(S^*)$ )

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From the algorithm 1, the simulations procedures are placed after applying the Local Search to evaluate the current local optimal solution ( $S^*$  and  $S^{**}$ ). These simulations consider a solution and a set of parameters such as convoys' speed and capacity. So, the SimILS algorithm obtains the corresponding simulated objective function,  $of(solution)$ , because it manages to compute the number of backorders for each period. Therefore, the main function of the simulation is to estimate the expected cost value of a newly generated solution. Next, we present algorithm 2 that summarizes the application of the SimILS algorithm as well as the introduced weights inserted in the objective function's terms.

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**Algorithm 2** The complete SimILS Algorithm

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1:  $(S_0) \leftarrow$  Generate_Initial_Solution
2:  $(S') \leftarrow$  Execute the SimILS( $S_0, W_{Priority\_routes\_weights}$ )
3:  $(S^*) \leftarrow$  Execute the SimILS( $S', W_{Priority\_SQL\_weights}$ )
4: Return Best_Sol( $S^*$ )

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The algorithm 2 shows that the SimILS procedure is applied twice with different inputs and objectives. In the first phase, the method seeks a solution ( $S'$ ) with reduced number of routes. Indeed, a solution with bigger number of routes than the current company's solution is not feasible for the company. Consequently, fictitious high weights are introduced on the routes' and the distances' terms, and low fictitious weight is assigned to the backorders one. It is done to force the reduction of the number of routes and the total routes' distance.

Afterward, the SimILS procedure is repeated, but based on the solution ( $S'$ ), which was previously computed, and different fictitious weights. The new weights are related to the Service-Quality-Level (SQL). The SQL is defined as the rate between the number of orders supplied at the correct period per the total of orders received during all considered periods. The SQL is an important concept that will be approached further ahead. As a result, the SimILS algorithm is forced to improve the backorders

indicator without increasing the number of routes and the total routes' distance. As a result, the output solution is a trade-off between those three considered elements placed in the Objective function. Next, we place comments over each one of the four components of the SimILS algorithm.

### 1. Compute an initial solution

An initial feasible solution is obtained through a greedy algorithm, in which each workshop's aisle is viewed as a route. So, on the one hand, the initial solution will have many routes. On the other hand, these routes are sequenced correctly. That is viewed as an advantage because the workstations are supposed to be visited in sequence. The initial solution is introduced through the method *Generate Initial Solution* in the algorithm 2.

### 2. Local Search

The local search methods considers both an Intra-Route Neighborhood Search (Intra-RNS) moves and Inter-RNS moves. The Intra-RNS consists of applying moves inside the same route. The Inter-RNS moves involve a set of nodes that moves between routes.

The Intra-RNS move applied is the *Or-optK* one, which refers to  $K$  adjacent nodes that are removed from a route and inserted in another position of the same route. Its computational complexity is  $O(n^2)$ . Later, the Inter-RNS moves that presented a positive impact on the local search are the *Shift (1,0)* and the *k-Shift*. The *Shift (1,0)* selects a unique node and inserts it in any position of the new route. The *k-Shift* move consists in selecting a subset of consecutive nodes  $K$  from a route  $A$  and inserting them at the end of a route  $B$ . In both moves, it must be checked the new route's capability to deliver the relocated demand, concerning the route's capacity. Notice that both Inter-RNS classes have the same computational complexity, which is  $O(n^2)$ .

As a result, the moves' strategy is defined based on Penna et al. (2013). However, a modification of the *k-Shift* movements is executed, which we called as *k-Shift-complete*. Even though a solution's cost is still an important acceptance criterion here, there are two main differences between this work's approach and the *k-Shift* and *Shift (1,0)* ones. The first variance concerns the confrontation between demand and capacity. On the one hand, the *k-Shift-complete* permits backorders to happen. On the other hand, it will penalize the objective function whenever it occurs. In contrast, the *k-Shift* and *Shift (1,0)* moves do not allow backorders. The second difference regards the nodes relocation from the original route into a second one. The *k-Shift-complete* places a subset of  $K$  consecutive nodes into all the possible locations of another route, including at the beginning and the end. By contrast, Penna et al. (2013) state the *k-Shift* places the transferred nodes at the end of a route only.

So, the *k-Shift-complete* is neither limiting the movement to a route's end location nor transferring only one node at each time.

To conclude, the SimILS takes into account the best improvement strategy, whenever the local search phase is executed, because the problem is considered as a strategical one and the execution time is not a relevant issue. An example of both Intra and Inter-RNS moves are illustrated in figure 5.

### 3. Simulation

To execute the simulation procedure, two main inputs are necessary, which are: (i) the fixed routes calculated in the Local Search phase, and (ii) the workstations' orders. Afterward, the simulation procedure discloses the results related to the primary KPIs, which are necessary to calculate a solution's objective function. Moreover, a set of secondary KPIs can also be calculated through the simulation. The secondary KPIs are out of the objective function calculation (see expression 1). However, it provides useful managerial insights to the logistics managers to evaluate a solution. The secondary KPIs

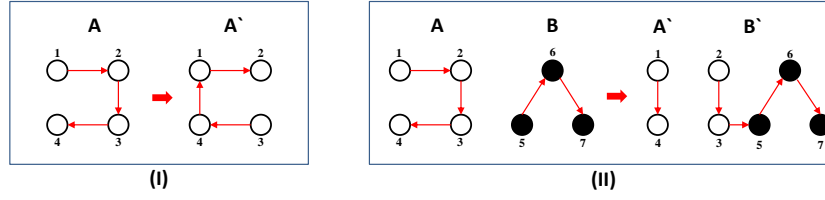


Fig. 5. An Or-opt2 (I) and a 2-Shift-complete (II) moves examples.

are defined as follows: (i) the total orders supplied; (ii) the total distance covered throughout the simulation; and (iii) the total of empty spots of the convoys that departed from the warehouse during the simulation. The simulation structure is presented by algorithm 3.

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### Algorithm 3 The Simulation Algorithm

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- 1:  $S^* \leftarrow$  Input Solution (Fixed Routes)
  - 2: **for** ( $p \in TotalofPeriods$ ) **do**
  - 3:   **for** ( $Route \in S^*$ ) **do**
  - 4:     Total\_Backorders += Get\_Back\_Orders(Route, p)
  - 5:     Total\_Supplied\_Route += Get\_Supplied(Route, p)
  - 6:     Total\_Dist\_Traveled += Get\_Distance\_Traveled(Route, p)
  - 7:     Total\_Empties\_Route += Get\_Empties(Route, p)
  - 8:   **end for**
  - 9: **end for**
  - 10: **Return** ( $of^{best\_sol}$ ) Simulated OF and KPIs.
- 

Here, all periods of the time horizon are considered. As a result, it is defined as the complete simulation (*Comp\_Sim*). The *Comp\_Sim* has its advantages and drawbacks. On the one hand, it may lead to a high computational effort, depending on the time horizon's size. On the other hand, it permits a complete evaluation of the time horizon considered. Therefore, the algorithm could assess extensively the solutions calculated by the Local Search phase. In this sense, *Comp\_Sim* is a suitable approach because the SimILS deals with a strategic problem.

Then, the Algorithm 1 executes the *Comp\_Sim* in three moments. The first one is placed at the beginning of the SimILS procedure to compute and save the  $of(Initial\_Solution)$ . Next, the *Comp\_Sim* is called after the LS phase to compute the  $of(Local\_Search)$ . Finally, the *Comp\_Sim* computes the  $of(Final\_Solution)$  to close the SimILS procedure. Note that the *Comp\_Sim* is responsible for calculating a solution's objective function value. Moreover, the **residual capacity rule**, stated in Section 2, is also considered here.

To conclude the *Comp\_Sim* description, we state that the algorithm 3 can be applied to assess any set of routes, such as the company's ones for example. As a result, it is a helpful tool to compare two different solutions.

#### 4. Perturbation phase

The perturbation procedure applied in this work is based on the Inter-RNS moves described previously. Considering previous experiments, the algorithm is set to run ten iterations during the pertur-

bation phase. Moreover, it has the same Inter-RNS moves' structure except for two main differences. First, on the one hand, the inter-RNS algorithm evaluates the solution's cost in order to decide if a new solution should be accepted or not. On the other hand, the perturbation procedure focus on a solution's Service-Quality Level (SQL) instead of its costs. So, a new route will be accepted in the solution as long as its SQL value is lower or equal to the defined SQL limit, which is set as 50% in this work. As a result, the SQL is a relevant indicator because it avoids low-SQL solutions, which could produce poor results at the local search phase further ahead. Then, the second divergence between the Local Search and the perturbation procedure refers to the way that the SQL is computed. So, all periods are simulated during the computation of the objective function, which we call a complete simulation. Differently, a partial simulation (*Partial\_Sim*) is applied in the perturbation phase instead. The *Partial\_Sim* works over a single newly generate route only, which is the one created by the inter-RNS moves in the perturbation phase. The main idea is to perform a short simulation and reduce the computational effort during the simulations executions. So, a biased-random method was created to reduce the simulation iterations, in which all the periods are sorted in a decreasing manner, regarding its backorders values. So, the first item of the list will be the period that has the highest backorders value (likewise, the worst SQL result). That method was developed based on the work of Grasa et al. (2017).

In addition, there is another important criterion to take into account, which concerns the solution introduced in the perturbation procedure. It varies depending on the iteration that the SimILS algorithm is. So, the current solution ( $S^t$ ) will be the input up to the first half of the total of iterations. Afterward, the best solution found so far ( $S^*$ ) will be introduced.

#### 5. Acceptance Criterion and Stopping Criterion

The local search must compute a solution that meets the conditions that are presented by expression 18. This expression states that the newly generated solution must be either cheaper than the best solution found so far or present a better SQL up to the first half of the number of iterations. Later, only the cost criterion will be evaluated.

$$(of^{best\_sol} > of^{current\_sol}) \wedge (SQL^{of^{Best\_sol}} < SQL^{of^{current\_sol}} \vee it < Total\_it/2) \quad (18)$$

Concerning the stopping criterion, the main condition to interrupt the procedure is whenever the maximum number of iterations is achieved. The SimILS algorithm's maximum number of iterations value is presented in the appendix A1 at the end of this chapter.

### 4. Computational Experiments

The methods described in the previous sections are evaluated through two main computational experiments. The main goal of the first experiment is to compare the performance between the ILP model and the SimILS algorithm. The second experiment aims to compare the solutions provided by the SimILS algorithm and the company's actual solution.

The experiments were carried out on the Operational System Windows 7 Enterprise 64 bits, Intel Core i7-4810MQ, 2.80GHz, 8 cores and 16 GB of RAM as the maximum capacity. Moreover, the programming languages JAVA were used to build the SimILS algorithm. Also, the ILP was modeled through

AMPL language and was solved by CPLEX 12.8.0. Next, we present the instances.

#### 4.1. The instances

An instance is defined as the number of orders that a set of workstations (WST) requires over a determined time-horizon. So, one instance differs from another regarding the following aspects: (i) the set of WST considered; (ii) the number of orders; (iii) the SKU class (small boxes (SB) orders or large containers (LC) ones), and (iv) the time-horizon considered.

Next, for each SKU class, three groups of data were collected. The first group is called Test data, which is a particular subset composed of a selection of all the workshop's WST and their respective orders. By contrast, the second group considers all WST that composed the assembly line, as well as their respective orders; in the second group case, five working days were used. Finally, the third group of data is like the second one (all WST considered) but studying the demand during a larger time-horizon size, in this case, four weeks.

Furthermore, those orders were collected over two different periods in the year, which refer to different production levels and other intrinsic features. The orders were collected directly in the material management system of the company (SAP). The table 2 summarizes the instances' characteristics, and the data's details are presented in the table A1.

Table 2

The summary of the instances' structure. In this table there are the following indications, concerning the data clustering strategy: (1) test data; (2) real data with five-days time horizon; and (3) real data with a four-weeks time horizon. Next, the **Item** column refers to the name of the instances; the **Material Type** refers to an instance's SKU class; the column **Days** refers to the instance's number of days; column **Period** represents the number of periods an instance considers; the **WST** refers an instance's total of workstations considered. The \* marker highlights the real-world instances.

Class (Group)	Item	Material Type	Days	Periods	WSTs
Test Data(1)	1-3		5	105	10
	4-6		5	105	15
	7-9	Small	5	105	20
Real Data(2)	10*	Boxes	5	105	123
Real Data(3)	11*		22	420	122
Test Data(1)	12-14		5	105	10
	15-17		5	105	15
	18-20	Large	5	105	20
Real Data(2)	21*	Containers	5	105	127
Real Data(3)	22*		22	420	126

The parameters used in the experiments are either set by the company (e.g., cost values or vehicles capacity) or obtained via preliminary experiments (e.g., total of iterations in the perturbation phase). The parameters used in the experiments are indicated in table A1. Moreover, a C++ code procedure was developed to build a distance matrix. That matrix presents the minimum distance from one workstation to the others, considering the workshop layout.

As mentioned, two main experiments are performed in this work. Experiment 1 aims to evaluate the performance between the ILP model and the SimILS algorithm approaches through a subset of WST and their respective demands. Note that the ILP is known to provide-proved optimal solutions. Also, the ILS has been successfully applied to complex Combinatorial Optimization problems, see Lourenço et al. (2019). Moreover, each method's performance is measured based on the objective function value, given by expression 1, and computational time. The data applied is the Test data class (1), see in Table 2.

Afterward, experiment 2 is conducted to evaluate real and complete instances. In this experiment, we take each one of the real historical data (2) and (3) and split it, chronologically, in two parts. The data set clustering idea illustrated by Figure 6.

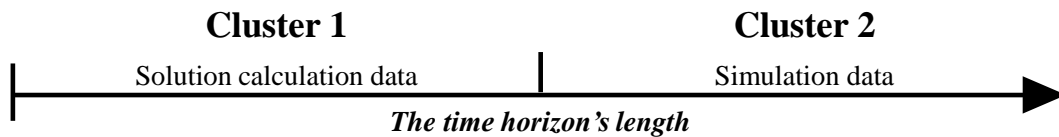


Fig. 6. The data clustering scheme. The first cluster gives support for the routes optimization. Then, the second cluster's major purpose is to evaluate the previous solution obtained. Each cluster is composed of orders that were introduced over a chronological fashion. Then, the first cluster refers to the first half of the sequenced orders. Likewise, cluster 2 refers to the second half left.

The first part is called cluster 1. Then, the cluster 1 data is inserted in the SimILS algorithm as an input to calculates a set of fixed routes. Later, the second phase of experiment 2 starts. It refers to the application of the second part left of the real historical data (2) and (3). The goal is to simulate the cluster 1's solution over a different set of data. Consequently, we will evaluate how the computed fixed set of routes perform under a new set of orders. Then, we compute the SimILS algorithm solution's KPIs and compare them with the KPIs of the company's solution. Note that the simulation procedure (algorithm 3) is applied to the current fixed solutions used in the company also. Table 3 resumes the experiments conducted.

Table 3  
The summary of the instances' structure.

Item	Method	Data
1	ILP vs. SimILS	Test Data (A subset of workstations)
2	SimILS_sol vs.Current_sol	Real Data (Phases 1 and 2)

Consequently, the main goal of Experiment 2 is to compute a solution to the ILRP, which provides a satisfactory set of fixed routes to cope with an actual stochastic system over an internal logistics context. Next, we present each experiment.



#### 4.2. The Experiment 1

Experiment 1's goal is to compare the results provided by the ILP model and the SimILS algorithm. These methods have the same objective function expression. As a result, they will be evaluated based on the objective function values and computational time. The results related to the experiment 1 are presented in the tables 4 and 5. First, we present the SB results and, then we present the LC ones.

Table 4

The Summary of the small boxes Experiment 1's results. The bolded values represent optimal solutions. The (\*) marker indicates that no feasible solution was provided. The R. refers to the number of routes. Also, the  $GAP_{met.}$  term refers to the comparison between the values computed by the ILP and SimILS. It is computed as  $(ILP_{Value}/SimILS_{Value} - 1)$ .

Item	WST	Method	OF Value	R.	Distance (m)	Back Orders	GAP cplex(%)	Time (sec)
1	10	ILP	<b>1459,8</b>	1	1359,8	0	0%	16
1	10	SimILS	1607,2	1	1507,2	0	-	6
$GAP_{met.}$			10%		11%	0%	-	
2	10	ILP	<b>1953,9</b>	1	1853,9	0	0%	12
2	10	SimILS	1956,3	1	1856,3	0	-	5
$GAP_{met.}$			0,1%		0%	0.1%	-	
3	10	ILP	<b>2308,9</b>	1	1853,9	355	0%	37
3	10	SimILS	2311,3	1	1856,3	355	-	6
$GAP_{met.}$			0.1%		0%	0.1%	-	
4	15	ILP	<b>1686,9</b>	1	1586,9	0	0%	2219
4	15	SimILS	1741,4	1	1641,4	0	-	6
$GAP_{met.}$			3%		3%	0%	-	
5	15	ILP	2020,4	1	1920,4	0	14%	7200
5	15	SimILS	2032,3	1	1932,3	0	-	6
$GAP_{met.}$			1%		1%	0%	-	
6	15	ILP	2247,18	1	2147,2	0	15%	7200
6	15	SimILS	2251,1	1	2151,0	0	-	5
$GAP_{met.}$			0.2%		0.2%	-	-	
7	20	ILP	(*)	(*)	(*)	(*)	(*)	(*)
7	20	SimILS	2357,2	1	2257,2	0	-	8
8	20	ILP	(*)	(*)	(*)	(*)	(*)	(*)
8	20	SimILS	2002,7	1	1902,7	0	-	11
9	20	ILP	(*)	(*)	(*)	(*)	(*)	(*)
9	20	SimILS	2247,2	1	2147,2	0	-	7

So, the ILP model found the optimal solution for four out of nine small boxes (SB) class instances; two feasible solutions with about 14.5% gap were computed; and the model could not find any feasible solution for the three instances left. Likewise, nine ILP experiments were conducted for large containers (LC) instances. Then, the ILP model found the optimal solution for three instances; three feasible solu-

Table 5

The Summary of the Large Containers Experiment 1's results. The bolded values represent optimal solutions. The (\*) marker indicates that no feasible solution was provided. The R. refers to the number of routes. Also, the  $GAP_{met.}$  term refers to the comparison between the values computed by the ILP and SimILS. It is computed as  $(ILP_{Value}/SimILS_{Value} - 1)$ .

Item	WST	Method	OF Value	R.	Distance (m)	Back Orders	GAP cplex(%)	Time (sec)
12	10	ILP	<b>1100,4</b>	1	997,49	3	0%	16
12	10	SimILS	1150,4	1	1047,4	3	-	5
$GAP_{met.}$			5%		5%	0%	-	
13	10	ILP	<b>1317,2</b>	1	1217,2	0	0%	17
13	10	SimILS	<b>1317,2</b>	1	1217,2	0	-	7
$GAP_{met.}$			<b>0%</b>		0%	0%	-	
14	10	ILP	<b>1349,2</b>	1	1217,2	32	0%	34
14	10	SimILS	<b>1349,2</b>	1	1217,2	32	-	9
$GAP_{met.}$			<b>0%</b>		0%	0%	-	
15	15	ILP	1409,2	1	1132,2	177	13%	7200
15	15	SimILS	1293,9	1	1144,9	49	-	11
$GAP_{met.}$			-8%		1%	-72%	-	
16	15	ILP	1670,9	1	1493,9	77	26%	7200
16	15	SimILS	1509,4	1	1362,4	47	-	9
$GAP_{met.}$			-10%		-9%	-39%	-	
17	15	ILP	2126,3	2	1920,3	6	21%	7200
17	15	SimILS	1959,5	1	1765,5	94	-	7
$GAP_{met.}$			-8%		-8%	1467%	-	
18	20	ILP	(*)	(*)	(*)	(*)	(*)	(*)
18	20	SimILS	4756,5	1	1492,5	3164	-	10
19	20	ILP	(*)	(*)	(*)	(*)	(*)	(*)
19	20	SimILS	2658,5	1	2288,5	270	-	8
20	20	ILP	(*)	(*)	(*)	(*)	(*)	(*)
20	20	SimILS	4260,1	1	2537,1	1623	-	11

tions with about 20% gap were computed, and the model could not find any feasible solution for three instances left.

Concerning the SimILS algorithm's results, the algorithm was able to find feasible solutions for all tested instances. Precisely, two of these solutions were optimal ones, as proved by the ILP.

As a result, the ILP and SimILS algorithm methods were compared, taking into account the optimal solutions provided by the ILP. For those optimal solutions, the GAP between the methods' solutions has been smaller or equal than 5% for six out of seven optimal solutions found. Note that the following expression was considered:  $GAP = (OF_{ILP}/OF_{SimILS}) - 1$ .

Concluding, although the ILP model can manage to compute the better solutions in the easiest in-

stances, the SimILS algorithm outperformed the ILS in the most complicated ones in a very short computational time. Notice also that the ILP model did not provide solutions for the larger instances (20 WST). Therefore, the SimILS algorithm is able to provide good results in a short time making this algorithm a proper one to deal with more complicated or real-world instances, like those applied in experiment 2.

### 4.3. The Experiment 2

Here, the objective is to compare the performance between the company's set of routes and the solutions computed through the SimILS algorithm. To better explain those experiments, this section is divided into two parts. The first part refers to a solution calculation applying the cluster 1 concept, see Figure 6. Then, the second part refers to solutions evaluation through the simulation of cluster 1's solution over the cluster 2 data.

#### 4.3.1. Solution Calculation Experiments - Cluster 1

Table 6 presents both the results computed by the SimILS algorithm. Also, it presents the results provided by the simulation of the company's current routes.

Table 6

The summary of the experiments 2's result - cluster 1. The first column refers to an instance's item and the second refers to the Material type. The LC means Large Containers and SB means Small Boxes. The third column refers to the cluster. The fourth column indicates the solution's origin. The fifth column depicts the OF's value. The sixth column presents the number of routes. The seventh column refers to the sum of all the solution's routes distance. The eighth column points out the backorders. The ninth column presents the total of orders supplied. The tenth column refers to the total of empties spots. The eleventh column presents the total distance traveled. Finally, the twelfth column refers to the computational time. Also, the  $GAP_{met.}$  term refers to the comparison between the values computed by the ILP and SimILS. It is computed as  $(CurrentValue/SimILSValue - 1)$ .

Item	M. Type	Cl	Routes' Class	OF	Routes (units)	Distance (meters)	Back Orders	T. Sup.	T. Emp. Spots	T. Traveled	Time (sec)
10	SB	1	Current	13.650,49	4	5.800	3.850	11.761	4.923	330.857	1
10	SB	1	SimILS	9.387,34	4	4.722	665	11.783	5.209	273.984	122
$GAP_{met.}$				-31%	-	-19%	-83%	0%	6%	-17%	
11	SB	1	Current	325.703,12	4	3.912	317.791	50.981	20.876	911.764	1
11	SB	1	SimILS	188.375,84	4	5.223	179.152	52.862	6.105	1.064.024	547
$GAP_{met.}$				-42%	-	34%	-44%	4%	-71%	17%	
21	LC	1	Current	18.506,60	6	8.313	4.194	3.152	275	1.052.110	1
21	LC	1	SimILS	11.482,32	6	5.214	268	3.256	504	768.700	137
$GAP_{met.}$				-38%	-	-37%	-94%	3%	83%	-27%	
22	LC	1	Current	210.550,79	6	6.862	197.689	13.222	1.240	3.394.932	1
22	LC	1	SimILS	82.677,43	6	5.221	71.456	14.680	1.143	3.270.752	784
$GAP_{met.}$				-61%	-	-24%	-64%	11%	-8%	-4%	

### 4.3.2. Solution Evaluation Experiments - Cluster 2

To conclude the experiment 2's executions, the second phase of tests is presented. Here, the goal is to evaluate the solution computed before (cluster 1) into a new set of data (cluster 2). As a result, both SimILS solutions and the company's current solution are simulated based on the cluster 2 data basis. Table 7 presents the results.

Table 7

The summary of the experiments 2's result - cluster 2. The first column refers to an instance's item and the second refers to the Material type. The LC means Large Containers and SB means Small Boxes. The third column refers to the cluster. The fourth column indicates the solution's origin. The fifth column depicts the OF's value. The sixth column presents the number of routes. The seventh column refers to the sum of all the solution's routes distance. The eighth column points out the backorders. The ninth column presents the total of orders supplied. The tenth column refers to the total of empties spots. The eleventh column presents the total distance traveled. Finally, the twelfth column refers to the computational time. Also, the  $GAP_{met.}$  term refers to the comparison between the values computed by the ILP and SimILS. It is computed as  $(Current_{value}/SimILS_{value} - 1)$ .

Item	M. Type	Cl	Routes' Class	OF	Routes (units)	Distance (meters)	Back Orders	T. Sup.	T. Emp. Spots	T. Traveled	Time (sec)
10	SB	2	Current	14.018,49	4	5.800	4.218	8.642	3.303	235.034	1
10	SB	2	SimILS	9.612,34	4	4.722	890	8.773	3.251	192.253	1
$GAP_{met.}$				-31%	-	-19%	-79%	2%	-2%	-18%	
11	SB	2	Current	206.902,12	4	3.912	198.990	51.763	20.455	908.962	1
11	SB	2	SimILS	146.387,44	4	5.223	137.165	52.681	5.278	1.046.986	1
$GAP_{met.}$				-29%	-	34%	-31%	2%	-74%	15%	
21	LC	2	Current	17.273,60	6	8.313	1.619	1.857	271	702.664	1
21	LC	2	SimILS	11.442,32	6	5.214	228	2.416	352	559.594	1
$GAP_{met.}$				-34%	-	-37%	-86%	30%	30%	-20%	
22	LC	2	Current	153.324,79	6	6.862	140.463	13.404	1.250	3.439.588	1
22	LC	2	SimILS	46.669,43	6	5.221	35.448	14.606	1.097	3.247.471	1
$GAP_{met.}$				-70%	-	-24%	-75%	9%	-12%	-6%	

Regarding the analysis of the results, the SimILS method outperformed the company's solutions. It can be confirmed by each objective function's indicators. Moreover, the secondary KPIs were improved in most of the cases as well. Even though the both solutions present the same number of routes for each instance, the reader may notice that the SimILS's solutions presented a better objective values in all tested instances. The difference between the SimILS routes and the company's ones relies on two premises. The first premise concerns with how the high/low turnover materials are faced. The company prefers set routes that join workstations, which receive materials with related consumption rate. On the contrary, this work did not take it into account to compute solutions. As a result, materials with different consumption rates are allowed to be mixed in the same route in this work

The second premise concerns the workstations clustering as well, but focus on its locations instead. The company usually does not merge workstations from different areas, or logistics groups, in the same route. By contrast, this work did not take into account any clustering limitation rule.

## 5. Conclusion

This work considers a real problem in a real car-assembling company that consists of finding the best supply routes from the warehouse to workstations, which are located along an assembly line. These routes are maintained fixed for an extensive period. However, demand is unknown. The objective is to support the company to compute routes that are cost-efficient and do not lead to delays in production. To the best of the authors' knowledge, a brand-new problem to the VRP literature is presented, which is called the **In-house Logistics Routing Problem**. That problem is compound by a set of premises stated as follow: (i) the stochastic and unknown demand; (ii) the self-ask-supply approach; (iii) the long-term and fixed routes; (iv) the driver must return to the depot after concluding the route; (v) requests are made throughout the time-horizon; (vi) time-window constraints; (vii) backorders are allowed; (viii) each customer is assigned to a route; (ix) the fixed-customer-sequence definition; (x) capacitated; and (xi) homogeneous fleet. That problem is not limited to SEAT application, but all companies that share similar concepts in their supplying/delivering processes.

So, both an ILP model to a deterministic version of the problem and a SimILS algorithm were proposed to calculate suitable fixed routes. Also, a comparison between these two approaches was performed. According to the results, the SimILS algorithm obtained excellent solutions, in particular for the larger instances.

A second experiment was conducted. It compared the solutions obtained by the SimILS with the actual company solution, using large and real data (historical data). For those cases, the SimILS algorithm obtained the best overall results, considering the objective function values and computational time. Moreover, taking into account the KPIs presented by the company, the SimILS algorithm presented better performance than the company's solutions in all the real-world instances evaluated.

As a result, it is possible to state that this work presents a valuable methodology to be applied to any car-assembling company. Indeed, the methodology and the results received positive and valuable feedback from the company's experts, who found it novel and interesting. So, the third conclusion refers to the remarkable contribution to the company, as depicted by the results presented as well as the introduction of applied Operational Research methods into the strategical processes of the company.

As future work, methods that are able to solve optimally large instances of the In-house Logistics Routing Problem should be explored, such as the branch-and-cut procedure. Moreover, extensions of the SimILS algorithms and the simulation procedure may be improved by adding a more realistic aspect, such as the traffic on the assembly-lines and the use of a different type of vehicles.

Finally, concerning the real application, it would be quite interesting studying the introduction of alternatives systems that do not count with the logistics operator as the one responsible for placing orders but an automatic-placing-order system. That study should also evaluate the most suitable management procedure to regulate the logistics flows based on that new scenario.

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## Appendix A

Table A1  
 Appendix A: Summary of the SimILS algorithm's parameters structure.

Data	Application	SimILS Parameters	
		1st phase	2nd phase
Number of Iteration	ILS	8	8
Number of Iteration	LS	8	8
Fictitious Weight	Route	1,000	1,000
Fictitious Weight	Distance	100	1
Fictitious Weight	Backorders	0.08	1
Max K-value	The LS moves		10 nodes
Convoy Speed	All cases		7 km/h
Convoy Capacity	Large Boxes		4
Convoy Capacity	Small Boxes		48
Placing a Large SKU	Large Boxes		2.69 min
Placing a Small SKU	Small Boxes		0.66 min