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► To cite this version:

Sana Frifita, Hasan Murat Afsar, Faicel Hnaien. A robust optimization approach for disassembly assembly routing problem under uncertain yields. *Expert Systems with Applications*, 2022, 202, pp.117304. 10.1016/j.eswa.2022.117304 . hal-04092405

HAL Id: hal-04092405

<https://utt.hal.science/hal-04092405v1>

Submitted on 22 Jul 2024

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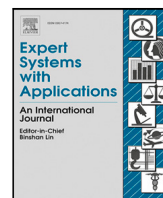


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Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Review

A robust optimization approach for disassembly assembly routing problem under uncertain yields

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ARTICLE INFO

Keywords:

Assembly and disassembly operations
Routing problem
Yields uncertainty
Discrete scenarios
Integer programming
Matheuristic

ABSTRACT

This study examines a stochastic disassembly assembly routing problem with returns (SDARP-R), in which disassembly yields are considered uncertain due to the unknown status of the returned products. We introduce a new formulation for the robust SDARP-R defined by discrete scenarios. We address five hypotheses, where different levels of decision flexibility are given. Analyses indicate that allowing flexibility in the procurement process improves the total cost but increases the difficulty of solving the problem, as well. However, allowing flexibility only to purchasing decisions is the most practical to the industry. An efficient matheuristic method based on integer programming and the Variable Neighborhood Search algorithm is also developed. The performance of the matheuristic method is evaluated through numerical tests, under three most promising hypothesis.

1. Introduction

Over the last years, reverse logistics has received increasing attention of industry practitioners and academic researchers (Govindan et al., 2015; Sheu et al., 2005). This is for environmental as well as economic reasons. One of the main environmental concerns is the increasing rate of waste production, which is leading to the saturation of landfills. For example, in the European Union, 3 billion tons of waste are thrown away each year, including 90 million tons of hazardous products. Large quantities of waste can cause significant public health and environmental problems such as the accelerate of pollution, global warming and the depletion of natural resources. To address these problems, governments are imposing new and stricter environmental regulations that require manufacturers to recover their end-of-life products through a reverse logistics network. Companies can not only comply with legal regulations but also utilize the remaining economic value contained in end-of-life products through various product recovery options, including reuse, recycling, repackaging, disposal, etc. Many companies are interested in recycling any unwanted items. The management of product recovery involves the management of all products, components and materials that are under the responsibility of a manufacturing company. The objectives are to recover as much economic and ecological value as is reasonably possible, thus reducing the amount of ultimate waste. The disassembly of returned products is the first step in product recovery. It allows the recovery of products at

the end of their life. Gupta and Taleb (1994) define this process as a systematic method for separating the product into modules, components, sub-assemblies or other groupings. In this process, a set of components of different qualities are obtained that can be reused or discarded. The reuse of used components helps to reduce pollution emissions, consumption of natural resources and to make production processes more environmentally. For this reason, several kinds of research studied the problems of reusable disassembled parts in different contexts, such as the automotive industry (Mathiyazhagan et al., 2018), cell phones (Sawanishi et al., 2015), food industry (Accorsi et al., 2020), etc. Despite the motivations and advantages of this reverse logistic, its implementation is still complicated. Indeed, there are still certain levels of uncertainty, particularly regarding the availability and the quality and quantity of returned products. Such uncertainty is influenced by many factors such as the bad returned product quality or the damage incurred during the disassembly operation. To reflect the variations in the quality of used components, the yield of the disassembly process, i.e. the quantities of components is assumed uncertain.

Since 1970, researchers prove that the supply chain made more effective and profitable through coordinating its activities via information sharing (Hein & Almeder, 2016), with particular emphasis on production and transport as two main supply chain activities. The lot-sizing problem (LSP) one of the famous production process problems, combined with the vehicle routing problem (VRP), represents a computational challenge for many researchers (Camargo et al., 2014; Fachini

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<https://doi.org/10.1016/j.eswa.2022.117304>

Received 28 May 2021; Received in revised form 4 March 2022; Accepted 22 April 2022

Available online 30 April 2022

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et al., 2017). The LSP allows the determination of the periods and the quantities to be produced to meet the demand for each period over a finite planning horizon, minimizing the sum of all the costs involved. The VRP involves designing optimal pick-up routes from geographically dispersed suppliers, subject to multiple constraints.

This study examines a multi-period dynamic disassembly assembly routing problem with returns (SDARP-R), in which the yields (r_i) are considered uncertain due to the unknown status of the returned products. To the best of our knowledge, no existing research has addressed this problem. From the real case, many factories produce items with new and used components disassembled from returned products (Guide, 2000). This kind of production system includes the disassembly and assembly operations that present complex issues regarding the structure of production costs. Taking uncertainty into account in the integrated decisions can make more sense but also increases the difficulty of the operational problems to be solved. This uncertainty may affect the production and procurement process. For this reason, different levels of flexibility are given to the different decisions related to these two supply chain activities that may or not be impacted by the scenarios. However, the system might not be able to satisfy the demand on time due to uncertainty on the quantities of the components. In this situation, the corresponding demand is lost incurring a high penalty cost.

The contributions of the current research are threefold:

1. We use the minimax robust optimization methodology introduced by Ben-Tal and Nemirovski (1998) to formulate a new problem, the robust SDARP-R. Each scenario corresponds to a vector of components' yield.
2. We propose a matheuristic algorithm to solve the robust SDARP-R under flexibility hypothesis.
3. We analyze impacts of different flexibility levels on the total cost.

The paper is organized as follows. Section 2 provides a literature review of related research. The optimization problem is formulated in Section 3. Section 4 presents the solution approach. The obtained results are provided and analyzed in Section 5. Section 6 gives concluding remarks.

2. Literature review

In the first part of the literature review, we briefly discuss the stochastic lot sizing problems. In the second part, we focus on the vehicle routing problem with stochastic demands. Finally, we give an overview of the integrated production management and vehicle routing problems in which uncertainties are taken into account.

2.1. Stochastic lot-sizing problems

The lot-sizing problem (LSP) introduced by Wagner and Whitin (1958) consists of making production and inventory decisions over a given planning horizon. Most of the literature considers the deterministic case of LSP, which can result in some cases wrong and costly decisions. Studying the stochastic case of the LSP (SLSP) is perhaps the most correct way to be attuned to reality. The SLSP papers mostly focus on demand as the source of uncertainty and few considered stochasticity in other elements such as cost, yield, lead-time and capacity. For the problem with stochastic demands, the service level constraint is one of the famous methods used by Bookbinder and Tan (1988). The authors proposed a chance constraint to model a service level constraint, and developed three strategies to handle the resulting setting, which are the static uncertainty, dynamic uncertainty and static-dynamic uncertainty. In like manner, Tempelmeier and Herpers (2011) solved a dynamic multi-item capacitated LSP under random period demands. Rossi et al. (2015) studied the SLSP in which the demand is assumed uncertain and non-stationary. They proposed four models

based on the static-dynamic uncertainty strategy, i.e. stochastic lot-sizing, α -service level constraints, penalty cost scheme, and β -service level constraints. The scenarios approach is also used to deal with the demand uncertainty in SLSP. Gutiérrez et al. (2004) addressed the single item SLSP where the costs and demand distribution depend on the scenario are considered. They solved the problem based on a branch-and-bound approach. Helber et al. (2013) used demand scenarios to approximate a nonlinear version of the SLSP. Machine breakdowns are assumed stochastic by Noureldin (2011) for the multi-period and multi-item SLSP. The proposed model includes a set of constraints to ensure some minimum probability of meeting the customer service level, and it is solved by a two-phase solution approach. Hnaïen and Afsar (2017) provided the min-max robust LSP with uncertain lead times. They explored the incapacitated and capacitated cases with and without lost sales, with discrete scenarios. Taş et al. (2019) formulated the LSP with stochastic setup times and overtime as a two-stage stochastic programming problem. They applied a sample average approximation procedure to obtain upper bounds and a statistical lower bound to evaluate the solutions of two proposed heuristics.

Recently, various research areas are studied the reverse LSP, which groups different activities such as disassembly, repair or recycling of end-life products. Among them, we focus on the disassembly process and especially the disassembly scheduling problem (DSP). Most of the related research treating the deterministic disassembly scheduling problem (Gupta & Taleb, 1994). For example, Kim et al. (2006) developed a two-phase heuristic where Langella (2007) presented an integer program and several heuristics to solve the problem. Compared to its deterministic counterpart, the literature on stochastic disassembly scheduling problem is still very scarce. As the SLSP, existing studies show interest in demand and/or yield uncertainty. Typically, the random yield does not necessarily the result of defective items, but it can also arise due to shortages from the suppliers (Moon et al., 2012).

There exist two approaches to represent random yield in a production context. The first group of research (e.g., Teunter and Flapper (2003)) represents random yield with a Bernoulli process, where a certain fraction of goods is defective, and the number of defective items depends on the lot size.

The second group of research (e.g., Salameh and Jaber (2000)) considered that all produced items are defective and random yields are modeled with a geometric distribution. Inderfurth and Langella (2006) proposed a one-to-one and a one-to-many heuristics to solve single-period DSP with yield uncertainty. Kongar and Gupta (2006) used a fuzzy goal programming technique to solve the disassembly to order system under uncertainty. They considered the uncertainty regarding the disassembly process by introducing various rates of broken, defective and replaced items. Barba-Gutiérrez and Adenso-Díaz (2009) extended the model proposed by Barba-Gutiérrez et al. (2008) by integrating demand uncertainty. To solve this problem, they proposed a fuzzy logic algorithm. Kim and Xirouchakis (2010) studied the DSP with stochastic demand and multiple product types with a two-level product structure. They proposed a stochastic inventory model and developed a Lagrangian relaxation method to solve it. After that, Wang and Huang (2013) considered demand uncertainty and they proposed a two-stage linear programming model using a scenario-based approach. Inderfurth et al. (2015) presented a two-root, three-leaf mathematical model that illustrates the effect of yield uncertainty in stochastically proportional and binomial models. Liu and Zhang (2018) dealt with a single-reference and multi-period disassembly scheduling problem with capacity constraint and with random yields and demands. This problem is formulated as a nonlinear mixed integer programming model also an algorithm based on an external approximation is proposed to solve it. A chance constraint approach is introduced to ensure that the probability of meeting the demand is greater than a predetermined service level and then approximated by a second order cone constraint.

2.2. Vehicle routing problem with stochastic demands

In this work, the quantities of disassembled components are assumed uncertain. This uncertainty is compensated by the purchase of new components or the disassembly of the purchased returned products. Therefore, this uncertainty impacts the collected quantity of returned products and components. Thus, this problem corresponds to the vehicle routing problem (VRP) with stochastic demand (Tillman, 1969).

The VRP is one of the famous optimization problems in logistics. In the VRP, a set of vehicles is available for serving a set of customers with demands. Of the studies that focus on the VRP with stochastic demands (VRPSD), several different mathematical models and algorithms are proposed and explored (Gendreau et al., 2016). Sungur et al. (2008) introduced a robust optimization approach to solve the VRPSD. The goal is to minimize transportation costs while satisfying all demands in a given bounded uncertainty set. Lei et al. (2011) formulated a two-stage stochastic recourse model and proposed an adaptive large neighborhood search heuristic. Lee et al. (2012) investigated the VRP with two types of uncertainty sets with adjustable parameters for the possible realizations of travel time and demand. They proposed a Dantzig–Wolfe decomposition and a dynamic programming algorithm to solve the problem with data uncertainty. Marinaki and Marinakis (2016) developed a swarm optimization based algorithm hybridized with variable neighborhood search to solve the VRPSD. Different variants of VRPSD are studied such as VRPSD with time windows and VRPSD with pick-up and delivery. Li et al. (2010) considered the VRPTW with both stochastic travel times, service times, and introduced a chance-constrained and a stochastic recourse model. Zhang et al. (2016) studied the VRPTW involving stochastic demands and they proposed three probabilistic models to address on-time deliveries probability while minimizing the expected total cost. Hu et al. (2018) studied the VRPTW under demand and travel time uncertainty. They proposed a robust optimization model to tackle small-sized instances and a two-stage algorithm based on a modified adaptive variable neighborhood search heuristic to tackle large instances. Corso and Wallace (2015) handled demand uncertainty in pick-up and delivery problem using the genetic algorithm. Goodson et al. (2017) solved the multiple-vehicles case under the re-optimization approach with approximate dynamic programming methods. Florio et al. (2020) studied the single VRPSD with optimal restocking as a Markov decision process. A wait-and-see model is proposed and it is used within a parallel heuristic to solve larger literature instances with up to 150 nodes and with a Poisson distributed demands.

2.3. Integrated production management and vehicle routing

The inventory routing problem is a generalization of the VRP. It combines inventory management at the customer and vehicle routing without considering the production planning at the central plant (Bell et al., 1983). The production routing problem combines lot-sizing decisions, inventory management, and routing (Chandra, 1993). Both the IRP and PRP are NP-hard combinatorial problems where different variants are extensively studied by focusing on developing efficient algorithms. We will focus on the matheuristic approach that is one of the efficient methods used to solve integrated production and routing problem. For the deterministic version, Absi et al. (2015) provided a matheuristic approach to solve a production routing problem. In the latter, the production routing problem is split into classic production planning problem and vehicle routing problem. The lot sizing model includes a visiting cost to account for distribution step. Consistent with methods from literature, the iterative approach has the smallest CPU time (less than 2 s) for instances with one vehicle. However, for instances with large transportation costs, it has difficulties reaching the optimal solution. The lack of intensification techniques and the

weak method of diversification used may be the weak point of this approach. Russell (2017) proposed two mathematical programming-based heuristics to solve the PRP. The differences between the Absi et al. (2015) approach and the approaches proposed by Russell (2017) the manner in which vehicle routing costs are artificially incorporated, the use of predetermined routes, initial seed routes, and the vehicle routing methodology employed. These proposed multi-phase approaches achieve many new best-known solutions to test problems from the literature. However, scalability issues limit its application to large-scale problems having more than 100 retailers and a twenty-period planning horizon. Solyali and Sural (2017) proposed a multiphase heuristics to solve the PRP. In their studied, they considered the case where a plant produces and distributes a single item to multiple retailers over a multi-period time horizon. Results show that the matheuristic managed to find new best solutions for the 65% of benchmark instances at the expense of higher computing times on large instances.

A few numbers of researchers extended the integrated problem to other more complicated problem that considers the stochastic case. For instance, Babagolzadeh et al. (2020) addressed the stochastic IRP with energy and emission costs. They considered the quantity delivered to each retailer, the route for distribution of products and the lost sale cost depend on scenarios. They proposed a two-stage stochastic programming and a matheuristic algorithm based on iterated local search and a MILP to solve the problem under 65 scenarios from a real case studied. Gruler et al. (2020) proposed a hybrid approach that combines the Variable Neighborhood Search algorithm (VNS) with a simulation to solve the stochastic IRP with a single period and stock-out requirements. Adulyasak et al. (2015) studied the stochastic PRP under demand uncertainty. They considered that the production quantity, the quantity delivered to the customer, the amount of unmet demand at customer depend on scenarios. They proposed a two-stage formulation, multi-stage problems, a bender decomposition-based branch-and-cut approach and a sample average approximation method to solve the problem with 100, 500, and 1000 scenarios. Results on instances with a large number of scenarios, show that their approaches provide significant solution speed improvements compared to a classical branch and cut algorithm. Other work studies the same problem such as the work of Shuang et al. (2019). They considered that the number of worn-out items available for pickup at customer and the number of worn-out items shipped from the customer to remanufacturing facility depends on scenarios. They proposed a two-stage stochastic MILP and generate three scenarios.

Recently, Chitsaz et al. (2019) studied the assembly routing problem (ARP) as an extension of the PRP. It presents the case of the collection of all the needed components from various suppliers to accomplish the assembly process, which is interrupted if a component is missing. ARP aims to minimize the sum of costs such as production, inventory, and procurement; subject to several types of capacity constraints over a finite and discrete-time horizon. They formulated the ARP as a mixed-integer linear programming model solved by a three-phase decomposition matheuristic. Afsar and Hnaïen (2020) proposed a new formulation for the same problem but with dynamic aspect of demand.

In Table 1 we present a summary of the works closest to the problems studied in this article. Based on this table, we observe that the assembly routing problem, one of the most important problems in the supply chain, is received less attention. To the best of our knowledge, Frifita et al. (2021) are the first authors that considered the disassembly assembly routing problem, where the yields are uncertain due to the unknown situation of returned products. They introduced the formulation of the robust dynamic disassembly assembly routing problem with returns defined by discrete scenarios. However, they addressed only instances with 14 nodes under 20 scenarios. Motivated by the above observations, this paper is devoted to the studied of this new planning problem that combines assembly and disassembly operations with vehicle routing in the stochastic case.

Table 1
Articles on assembly and disassembly problems.

| References | Assembly | | Disassembly | | | Transport | Resolution methods |
|------------------------------------|------------|----------|-------------|----------|------------|-----------|--|
| | Multi-item | Capacity | Multi-item | Capacity | Stochastic | LTL | |
| Kim and Xirouchakis (2010) | | | * | * | * | | Lagrangian heuristic |
| Prakash et al. (2012) | | | | * | * | | Constraint-based simulated annealing algorithm |
| Ullrich and Buscher (2013) | | | | * | * | | Heuristics |
| Godichaud et al. (2015) | | | | * | * | | MILP, Genetic algorithm |
| Inderfurth et al. (2015) | | | | | * | | Empirical analysis |
| Hein and Almeder (2016) | | * | | | | * | MILP |
| Hrouga et al. (2016) | | | | * | * | | Genetic algorithm, Fix-and-optimize |
| Ji et al. (2016) | | | * | * | * | | Lagrangian heuristic |
| Díaz-Madroño et al. (2017) | * | * | | | * | | MILP |
| Liu and Zhang (2018) | | | | * | * | | Nonlinear programming, Outer approximation |
| Tian and Zhang (2019) | | | * | * | * | | Particle swarm optimization algorithm |
| Habibi et al. (2019) | | | * | * | * | * | MILP, matheuristic |
| Chitsaz et al. (2019) | | * | | | | * | MILP, matheuristic |
| Chitsaz et al. (2020) | | | | | | * | branch-and-cut |
| Slama et al. (2020) | | | * | * | * | | MILP |
| Afsar and Hnaïen (2020) | | | | | | * | MILP, Benders decomposition |
| Pour-Massahian-Tafti et al. (2020) | | | | * | * | | 3 MILP, Heuristics |
| Frifita et al. (2021) | | * | | * | * | * | MILP |

3. Robust disassembly assembly routing problem with returns

3.1. Problem description

We consider a single disassembly and assembly site having a common storage capacity C_0 for components, returned and new products. The production operation is done to satisfy the external demand, d_t , at each period t by assembling a set of new and disassembled components with respecting the plant's production capacity C . Lost sales are allowed in the model with a penalty cost (pr). Without loss of generality, we assume that one unit of each component is needed to make one unit of the new product. The location of suppliers and warehouses as well as the production plant is modeled as nodes on a directed symmetric graph $G = (N, A)$, with the node-set $N^+ = N \cup \{0\}$, where 0 represents the plant, and the arc set $A = \{(u, v) : u, v \in N^+, u \neq v\}$. Each arc (u, v) has a transportation cost $c_{uv} > 0$. The set of nodes regroups the suppliers who provide a unique component and warehouses in which there are a stock of unique type product to be disassembled. These products are either at the end of their useful lives or the end of their consumer use. A bijective function ψ defines the supplier of a component ($v = \psi(j)$).

Fig. 1 presents an example of the deterministic case of the studied problem. Depending on the demand d_t for a single type of finished products, the manufacturer will produce the necessary quantities at the periods $t = 2$ and $t = 3$ using one unit of each type of raw materials and used parts. These used parts are screened and recovered by disassembling the returned products. Returned products are located in limited quantity at warehouses. We, therefore, assume here that the returned products are sufficient for the acquisition process. For the demand of the first period, it is satisfied with the shortage of final product at the factory depot. Even if there is no production in the first period, the vehicles collect components to ensure the production in the later periods. Each component whether it is new or disassembled has a size b_i , the same for the new and returned products (b). Size is taken into account for vehicle and storage capacities during the planning. The total cost includes disassembly, assembly, inventories, lost sales, purchasing and routing costs. For each product produced or disassembled in a period, the incurred cost includes a setup cost. In this example, the r_t are assumed to be known, but in the stochastic case, it can take a binary value of 0 or 1.

In some cases, the quality of each type of disassembled parts cannot be known in advance. Therefore, we generated a set of scenarios with random yields. The scenarios are equiprobable and the yields follow the Bernoulli distribution law. All returned products have a two-level structure, which means that returned products and disassembled components are considered as root and leaf items, respectively. Each returned product has a unit size b the same as the new product. This size

influences the capacity of vehicles on routed and storage capacity of the plant. We consider a unit production cost f_t and setup cost f'_t at the plant level. We assume that an unlimited fleet of homogeneous vehicles with a capacity of Q is stationed at the plant, to pickup components and returned products from suppliers and warehouses represented by the set $N = \{1, \dots, n\}$. The planning horizon comprises T periods ($t \in \{1, \dots, |T|\}$) where the demand is known but dynamic in time, as are all the costs except transport.

3.2. Mathematical formulation

The full list of notations used throughout this paper is given in what follow:

- Sets:
 - T : Planning horizon $t \in \{1, \dots, |T|\}$.
 - N^+ : Set of nodes, $N^+ = \{0, \dots, n\}$, where 0 represents the plant.
 - N : Set of suppliers and specific depots that provide component and returned product, $N = N^+ \setminus \{0\}$.
 - A : Set of arcs, $A = \{(u, v) : u, v \in N^+, u \neq v\}$.
 - K : Set of components.
 - S : Set of scenarios.
- Decision variables:
 - p_t : Production quantity for period t at the plant.
 - y'_t : Equal to 1 if there is disassembly operation at the plant for period t , 0 otherwise.
 - y_t : Equal to 1 if there is production at the plant for period t , 0 otherwise.
 - Ir_t : Inventory of returned product at the plant at the end of period t .
 - I_t : Inventory of items at the plant at the end of period t .
 - Ic_{it}^s : Inventory of component i at the plant at the end of period t in scenario s .
 - x_{uvt} : Number of times a vehicle traverses the arc $(u, v) \in A$ for period t .
 - F_{uvt} : Forward vehicle load on the arc $(u, v) \in A$ for period t .
 - F_{vut} : Backward remaining vehicle capacity on the arc $(v, u) \in A$ for period t .
 - z_{ut} : Equal to 1 if node $u \in N$ is visited in period t , 0 otherwise.
 - q_{ut} : Shipment quantity of returned product from node $u \in N$ to the plant for period t .
 - qc_{ut} : Shipment quantity of components from node $u \in N$ to the plant for period t .
 - dis_t : Disassembly quantity of returned product at the plant for period t .
 - l_t : Quantity of lost sales at period t .

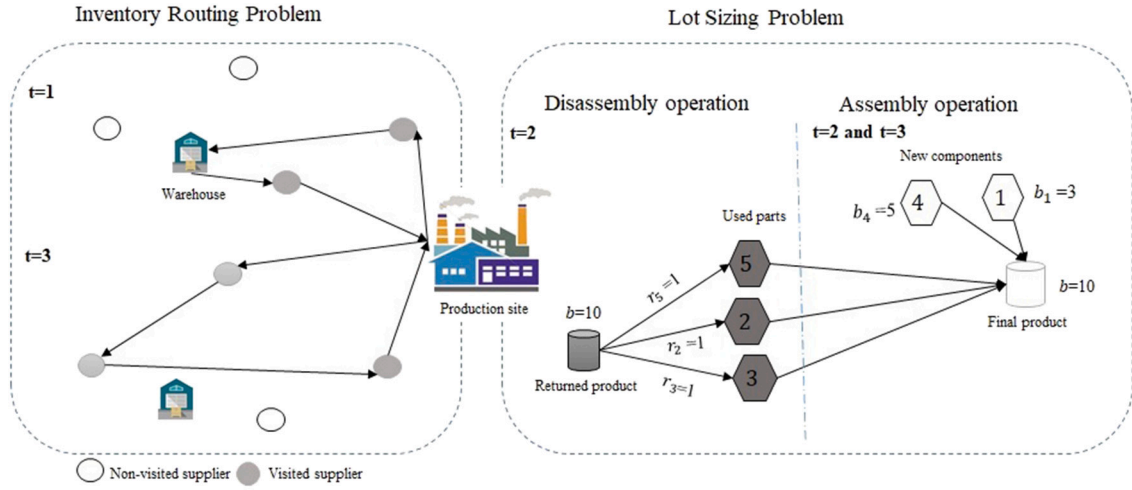


Fig. 1. Example of a SDARP-R instance.

• Parameters:

- f_t : Unit production cost for new items for period t .
- f'_t : Setup cost for new items for period t .
- a_{it}, ar_t : Unit purchase cost for component i and returned product for period t , respectively.
- h_t : Unit holding cost of new items and at the plant for period t .
- hr_t : Unit holding cost of returned product at the plant for period t .
- hc_{it} : Unit holding cost of component i at the plant for period t .
- c_{uv} : Transportation cost between nodes u and v , $(u, v) \in A$.
- C : Production capacity.
- C_0 : Global inventory capacity at the plant.
- Q : Vehicle capacity.
- S_{ut} : Supply of returned product at node $u \in N$ in period t .
- S_{cut} : Supply of component at node $u \in N$ for period t .
- r_i^s : Yield ratio of leaf item i to root item in scenario s .
- b_i : Unit size of component i .
- b : Unit size of product.
- d_t : Demand for the final products at the plant for period t .
- pr : Unit cost of lost sales.
- σ_{ut}^s : Approximated visiting cost at node $u \in N$ for period t in scenario s .

The minimax robust problem modifies the objective function of deterministic problem as minimax objective function after introducing a set of uncertain yields scenarios. We propose a mathematical model based on the two-commodity flow formulation (Afsar & Hnaien, 2020). The binary variable x_{uv} takes the value 1, if the arc (uv) is traversed (in any direction) in period t . The nodes 0 and $n+1$ correspond to the depot node. This model presents a Minimax objective function as follows:

$$\min \left(\sum_{t \in T} (f'_t(y_t + y'_t) + f_t p_t + pr l_t + hr_t I_r t + h_t I_t + \sum_{u \in N} ar_t q_{ut} + \sum_{i \in K} a_{it} q_{c_{\psi(i)t}} + \sum_{(u,v) \in A} c_{uv} x_{uv}) + \max_{s \in S} (\sum_{i \in K} hc_{it} I_{c_{it}^s}) \right) \quad (1)$$

s.t

$$I_{t-1} + p_t + l_t = d_t + I_t \quad \forall t \in T \quad (2)$$

$$l_t \leq d_t \quad \forall t \in T \quad (3)$$

$$I_{c_{it}^s} + q_{c_{\psi(i)t}} + r_i^s dis_t = p_t + I_{c_{it}^s} \quad \forall t \in T, \forall i \in K, \forall s \in S \quad (4)$$

$$I_{r_{t-1}} + \sum_{u \in N} q_{ut} = dis_t + I_r t \quad \forall t \in T \quad (5)$$

$$p_t \leq C y_t \quad \forall t \in T \quad (6)$$

$$dis_t \leq C y'_t \quad \forall t \in T \quad (7)$$

$$q_{ut} \leq S_{ut} \quad \forall t \in T, \forall u \in N \quad (8)$$

$$q_{cut} \leq S_{cut} \quad \forall t \in T, \forall u \in N \quad (9)$$

$$\sum_{i \in K} b_i I_{c_{it}^s} + b(I_t + I_r t) \leq C_0 \quad \forall t \in T, \forall s \in S \quad (10)$$

$$b_{\psi^{-1}(u)} q_{cut} + b q_{ut} \leq Q z_{ut} \quad \forall t \in T, \forall u \in N \quad (11)$$

$$\sum_{u \in N^+ | u \neq v} x_{uv} = \sum_{u \in N^+ | u \neq v} x_{vu} \quad \forall t \in T, \forall v \in N^+ \quad (12)$$

$$\sum_{u \in N^+} x_{uv} = z_{vt} \quad \forall t \in T, \forall v \in N \quad (13)$$

$$F_{uv} + F_{vu} = Q x_{uv} \quad \forall t \in T, \forall u \in N^+, \forall v \in N^+ | u \neq v \quad (14)$$

$$\sum_{v \in N^+} F_{uv} - \sum_{v \in N^+} F_{vu} = 2(b q_{ut} + b_{\psi^{-1}(u)} q_{cut}) \quad \forall t \in T, \forall u \in N \quad (15)$$

$$\sum_{u \in N} F_{0u} = \sum_{u \in N} b_{\psi^{-1}(u)} q_{cut} + \sum_{u \in N} b q_{ut} \quad \forall t \in T \quad (16)$$

$$\sum_{u \in N} Q x_{0u} - (\sum_{u \in N} b_{\psi^{-1}(u)} q_{cut} + \sum_{u \in N} b q_{ut}) = \sum_{u \in N} F_{u0} \quad \forall t \in T \quad (17)$$

$$\sum_{v \in N^+} F_{n+1v} = Q \sum_{v \in N^+} x_{0v} \quad \forall t \in T \quad (18)$$

$$p_t, dis_t, l_t \geq 0, y'_t, y_t \in \{0, 1\} \quad \forall t \in T, \forall u \in N \quad (19)$$

$$I_{c_{it}^s}, I_r t, I_t \geq 0 \quad \forall t \in T, \forall i \in K, \forall s \in S \quad (20)$$

$$q_{cut}, q_{ut} \geq 0 \quad \forall t \in T, \forall u \in N \quad (21)$$

$$F_{uv} \geq 0 \quad \forall t \in T, \forall u \in N^+, \forall v \in N^+ \quad (22)$$

$$z_{ut}, x_{uv} \in \{0, 1\} \quad \forall t \in T, \forall u \in N^+, \forall v \in N^+ \quad (23)$$

The objective function (1) minimizes the total setup (both disassembly and assembly operations), production, lost sales, inventory holding costs for new and returned products, purchase, and transportation costs as well as the maximum inventory holding costs of components over all scenarios. Only inventory costs of the plant are taken into account. The constraints from (2) to (11) are relevant to LSP with returns while the

constraints from (12) to (18) define the transportation problem. The constraints (2) ensure the manufactured final product inventory flow. The amount of the lost sales is less than the demand (constraint (3)). Constraints (4) and (5) ensure the components (new or disassembled) and returned product flow balance, respectively. Constraints (6) and (7) fix the setup decisions variables for the assembly and disassembly operations, respectively. Constraints (8) and (9) ensure that each visited node can provide the requested quantity of components or returned products. Constraints (10) limit the storage capacity of the final product, the components, and returned products at the plant. Constraints (11) impose the limit of total components and returned product shipment quantity from each node in each period by the vehicle capacity.

Constraints (12) state that the inflow is equal to the outflow at each node. Constraints (13) imply that if a node u is visited, there is only one arc (uv) is traversed by a vehicle. Constraints (14) state that the sum of forward vehicle load and the backward remaining capacity is equal to the total vehicle capacity at the traversed arc. The total change in forward vehicle load and the backward remaining capacity is twice the volume of the purchased amount from a visited node (constraints (15)). The forward vehicle load leaving the depot is equal to the total purchasing quantities (Constraints (16)). Constraints (17) state that the total backward remaining vehicle capacity re-entering depot node is the total capacity of all used vehicles minus the total volume of purchased components. Constraints (18) state that the total backward remaining capacity and the total capacity of used vehicles are equal. Constraints (19)–(23) are domain constraints.

The proposed model is nonlinear due to the nested min–max operator. We use ϕ to denote the maximum value of the components inventory cost at the plant. The mathematical model equivalent to the minimax model becomes the following linear programming model:

$$\min \sum_{i \in T} \left(f'_i(y_i + y'_i) + f_i p_i + p r l_i + h r_i I r_i + h_t I_t + \sum_{u \in N} a r_i q_{ut} + \sum_{i \in K} a_{it} q c_{\psi(i)t} + \sum_{(u,v) \in A} c_{uv} x_{uvt} \right) + \phi \tag{24}$$

s.t (2)–(23)

$$\sum_{i \in T} \sum_{i \in K} h c_{it} I c_{it}^s \leq \phi \quad \forall s \in S \tag{25}$$

3.3. Flexibility levels

We analyze the following five assumptions H_j to identify which new model's decisions variables are the most beneficial to have flexibility and be dependent on scenarios:

- H_0 (zero flexibility): no decision variable is dependent on scenarios $(p_t, l_t, dis_t^s, q_{ut}, qc_{ut}^s, x_{uvt})$. The preceding mixed integer linear model presents this flexibility level.
- H_1 : the production and lost sales related decisions are flexible and depend on scenarios (p_t^s, l_t^s, dis_t^s) . This hypothesis allows adding flexibility to production, which means that the quantities to be assembled and disassembled depend on scenarios.
- H_2 : the decisions of purchased quantities of returned products and components depend on scenarios (q_{ut}^s, qc_{ut}^s) .
- H_3 : procurement decisions that include the purchased quantities and the routing decisions depend on scenarios $(q_{ut}^s, qc_{ut}^s, x_{uvt}^s)$. This hypothesis enlarges the flexibility of H_2 by including routing decisions.
- H_4 : all decisions variables depend on scenarios $(p_t^s, l_t^s, dis_t^s, q_{ut}^s, qc_{ut}^s, x_{uvt}^s)$. In this hypothesis, production and procurement depend on scenarios.

4. Two-phase matheuristic approach

In this section, we present a matheuristic algorithm based on a MIP model and a VNS method for the proposed problem. Matheuristics are heuristic methods that make use of an exact methods inside heuristics framework. This method is successfully implemented in different optimization problems such as the PRP (Absi et al., 2015), the collection disassembly problem in the work of Habibi et al. (2017), and ARP in the work of Chitsaz et al. (2019).

The VNS method is an extension of the classical local search that includes shaking procedure as a diversification mechanism (Mladenović & Hansen, 1997). VNS is a single solution based method that searches in the neighborhood of the local optimum found by local search to generate a new best solution. According to Funke et al. (2005), local search and local search-based metaheuristics are currently among the best ways to solve large vehicle routing and scheduling problems. Although simple, VNS approach combines several local search neighborhoods and it is relatively easy-to-implement, do not contain a large number of parameters requiring time-consuming setting processes, and offer an excellent trade-off in terms of solutions quality as well as in terms of computing times (Frifita & Masmoudi, 2020). We can see it is employed in the most recent works on vehicle routing problems (e.g. Kuo et al. (2022) to solve VRP with drones and time windows, Guo et al. (2022) for VRP with ride-sharing, Xu and Cai (2018) to provide excellent solutions for consistent VRP). That is why we are motivated to use the VNS algorithm and we intended to combine it with a mixed integer programming to present matheuristic.

The proposed matheuristic (Fig. 2) performs two main steps. The first step consists in solving the assembly and disassembly problem (Step A). It is addressing the decisions of $dis_t^s, p_t, I c_t^s, q_{ut}^s, qc_{ut}^s, l_t,$ and z_{ut}^s . Using the value of z_{ut}^s , the set of nodes visited in each period and each scenario is obtained. Also, q_{ut}^s and qc_{ut}^s values reveal the shipped quantity that forms each node. The second step (Step B), is to solve the routing problem by VNS.

We first generate a lower bound of the total costs (the sum of production cost and transportation cost). Then we initialize the value of σ_{ut}^s according to the lower bound. The parameter σ_{ut}^s is used as an approximate visiting cost (updated throughout the algorithm) of collection from node u at period t under scenario s . Consecutively, the routing problem is solved and the routing cost is obtained. Once the route of all period is built, we implement a memorization process inspired from tabu search (Step C). At each iteration, we keep in memory the best transport solution found in step B. After that, the value of σ_{ut}^s is updated based on this solution and the objective function is recalculated (see Section 4.3). This step is followed by a procedure of update for the worst case (see Section 4.4). Before resolving the LSP we check if this solution already exists in the memory. If it does, we proceed to step E of the diversification mechanism. If not, we go to step A. This technique allows us to escape local optimums to speed up the resolution. The iterative procedure stops when a stopping criteria is reached (after 10 iterations without improvement). The whole scheme is repeated until a maximal number of iterations ($iter2_{max}$) is achieved.

In some cases, the time limit for MILP in step A gives solutions with a high gap value. This leads us to define a variable time limit that increases as soon as there are no cost improvements. Then, returns to its initial value.

In the following subsections, we describe the different steps of the proposed matheuristic.

4.1. MILP with approximated transportation cost

The (step A) is solved by a MILP which minimizes a set of costs as presented in Eq. (26). Those costs are the assembly, disassembly, lost

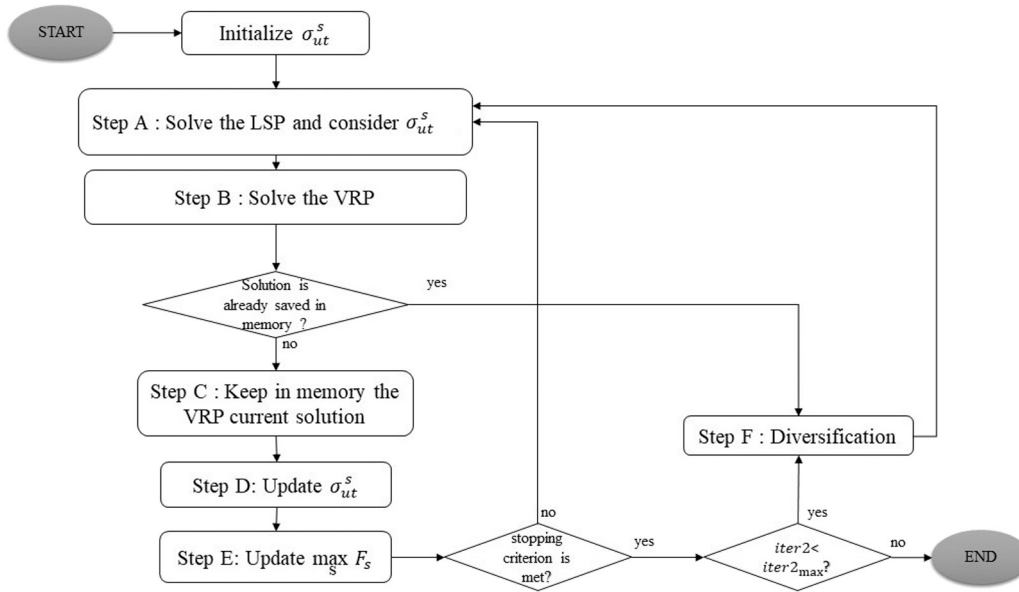


Fig. 2. The general steps of our algorithm.

sales, and inventories costs as well as an approximated transportation costs instead of the transportation costs over all scenarios.

$$\begin{aligned}
 \min \quad & (\sum_{i \in T} (f'_i(y_i + y'_i) + f_i p_i + pr l_i + hr_i I r_i + h_i I_i \\
 & + \max_{s \in S} (\sum_{i \in K} hc_{it} I c_{it}^s + \sum_{u \in N} ar_i q_{ut}^s + \sum_{i \in K} a_{it} q c_{\psi(i)t}^s + \tau_i^s)) \\
 \text{s.t.} \quad & (2)-(11)
 \end{aligned} \tag{26}$$

We note that $\tau_i^s = \sum_{u \in A} \sigma_{ut}^s z_{ut}^s$ is an approximated of the total transportation cost using the node visit variables z_{ut}^s and the approximated visiting cost σ_{ut}^s . This is the crucial link between production and transport problems.

4.2. Variable neighborhood search algorithm

Solving the problem with an approximate transport cost by the MILP allows us to have the set of visited nodes z_{ut}^s in each scenario as well as the purchased quantities of returned product q_{ut} and components $q c_{ut}$. Therefore, the routing and purchasing decision variables related to each period and each scenario are fixed as parameters for the VNS (Algorithm 1) to solve one VRP for each period and each scenario. The VNS was first proposed by [Mladenović and Hansen \(1997\)](#) and it takes into account a set of k_{max} neighborhoods and executes alternately a local search procedure and a shaking procedure to escape from the local optima. Our VNS starts with an initial solution obtained by applying a random construction heuristic. At each iteration, a random solution is generated from a current neighborhood and then a local search procedure is applied to improve the solution. If the new solution is better than the incumbent solution X_{best} , then the procedure is repeated by reinitializing the neighborhood, otherwise by passing to the next neighborhood. Four neighborhood structures are used both in local search and shaking procedures (see [Frifita et al. \(2020\)](#)):

- ShiftIntra; a node is removed from its current position to another position in the same route.
- Swapintra; two nodes from the same route are swapped.
- ShiftInter; a node is removed from one route to another one.
- Swapinter; two nodes from two different routes are swapped.

The local search strategy following a best improvement strategy. The above-mentioned movements are performed in constant time.

Algorithm 1 Variable Neighborhood Search algorithm

```

1:  $X$  =initial solution from the construction heuristic
2:  $X_{best} = X$ 
3: repeat
4:    $k = 1$ 
5:   while  $k < k_{max}$  do
6:      $X_1 = \text{Shake}(X, k)$ 
7:      $X_2 = \text{Local search}(X_1)$ 
8:     if  $f(X_2) < f(X)$  then
9:        $X_{best} = X_2$ 
10:       $k = 1$ 
11:    else
12:       $k++$ 
13:    end if
14:  end while
15: until  $iter > iter_{max}$ 
  
```

4.3. Approximated visiting cost

To update σ_{ut}^s we used two techniques: In the first technique, we suppose that u is a node visited in a route r of period t at scenario s obtained by solving Routing Problem. Let pre denote the predecessor of u with the cost c_{upre} and suc is its successor with the cost c_{usuc} . M_t^s is the set of nodes $u \in N$ for which $z_{ut}^s = 1$. If $u \in M_t^s$ then $\sigma_{ut}^s = c_{upre} + c_{usuc} - c_{psuc}$, which means that if a node u is eliminated from its current route, an acceptable route can be obtained by connecting the predecessor and successor nodes. Otherwise inserting u into the available vehicle routes in period t at scenario s , so $\sigma_{ut}^s = \Delta_{ut}^s$ where Δ_{ut}^s would be the cheapest insertion cost among all the routes in that period at the correspondent scenario s . Preliminary planning has shown that purchase and pickup of goods was not done in certain periods. So by inserting the node u in an unserved period t , an acceptable route can be obtained. With this technique, we impose visits to the nodes in different periods which can influence productions periods. The second technique divides the total transportation cost of the served period among the visited nodes. Let $cost_t^s$ be the total transportation cost in period t at scenario s , we define $\sigma_{ut}^s = cost_t^s (c_{0u} / \sum_{v \in M_t^s} c_{0v})$ if $u \in M_t^s$

Table 2
Results for a small instance with 4 scenarios.

| | s = 1 | s = 2 | s = 3 | s = 4 |
|--------------|---------------|--------|---------------|---------------|
| i = 1 | 17 188 | 15 902 | 17 053 | 16 327 |
| i = 2 | 16 570 | 15 851 | 16 465 | 15 885 |
| i = 3 | 16 639 | 15 933 | 15 775 | 15 921 |
| i = 4 | 16 639 | 15 851 | 15 738 | 15 977 |
| i = 5 | 16 534 | 15 851 | 16 501 | 15 921 |
| i = 6 | 15 839 | 15 968 | 16 093 | 15 885 |
| i = 7 | 17 188 | 15 887 | 17 053 | 16 363 |
| i = 8 | 15 839 | 15 881 | 15 738 | 15 885 |
| <i>bestF</i> | | | | 15 885 |

else $\sigma_{ut}^s = (cost_i^s + \Delta_{ut})(c_{0u} / \sum_{v \in M^s \cup \{u\}} c_{0v})$. One technique is used for a defined number of iterations ($iter1 = iter1_{max}$), and then we switch to the second one and vice versa. As results, most of the time we get better results compared to using any one of these two techniques alone.

4.4. Update the best worst cost procedure

The transportation solution provided by VNS presents the best set of routes for each scenario with the best costs. In step E, a procedure was defined to recalculate the true worst cost for each iteration i of the algorithm. In this procedure, we recalculate for each scenario s the total cost obtained by the MILP (f_i^s (MILP)) plus the transport cost obtained by the VNS (f_i^s (VNS)). Thus, $f_i^s = f_i^s$ (MILP) + f_i^s (VNS). This procedure allows to change the value of the best worst cost from one iteration to another. For each scenario $s \in \{1, \dots, |S|\}$, we compare two consecutive iterations i and $i+1$ keeping the minimum value $F_s = \min(f_i^s, f_{i+1}^s)$. We recover the maximum value $\max_{s=1..S} F_s$ on all scenarios S . For each iteration i , we update the worst cost corresponding to the minimum value given by $bestF = \min(\max_{s=1..S} F_s)$. If there is a change, we update the corresponding best solution. In the following example (Table 2), we present the value of the objective function recalculated by our algorithm for a number of scenarios equal to 4 and a number of iterations equal to 8. As a result, $bestF = 15 885$ is the worst cost among all the scenarios. The bold numbers in the table show the changes in the $\max_{s=1..S} F_s$ value between iterations.

4.5. Diversification mechanisms

To prevent a quick convergence to the best solution, two diversification mechanisms are used (Absi et al., 2015): a multi-start procedure and an update diversification mechanism. These two diversification mechanisms reinitialize visiting costs σ_{ut} and restarts the iterative procedure. At each iteration restart we randomly chose one of two mechanisms.

The multi-start procedure: reinitializes approximate visiting costs σ_{ut}^s through multiplication with a random value ϵ in $[0.5, 1.5]$ ($\sigma_{ut}^s = (c_{0u} + c_{0u}) * \epsilon$).

The update diversification mechanism modifies σ_{ut}^s according to the best known solution. It consists of multiplying σ_{ut}^s by the number of nodes served M_i^s plus one (to avoid zero multiplication) $\sigma_{ut}^s = |M_i^s| \sigma_{ut}^s + 1$.

5. Computational results

The matheuristic is coded in Java with Eclipse Version: 4.9.0. The Cplex library 12.9 is used within a java code to solve the mathematical models. All tests are run on HP desktop computer Intel (R) Core (TM) i7 2.9 GHz with 16 GO of RAM on Windows 10 (64-bit). We note that the statistical tests are performed with IBM SPSS Statistics software. The main parameters of the algorithm $iter1_{max}$ and $iter2_{max}$ are carefully tuned as they impact on the quality of the solution and computational time. They are fixed with the Friedman test by using *Minitab.18* software. The results value are equal to 5 for $iter1_{max}$ and

20 for $iter2_{max}$. The time limit for solving each instance by CPLEX is set to one hour (3600 s). For the limit of the execution time for CPLEX in the matheuristic, we impose between 60 and 120 s. The value of the maximum VNS iteration $iter_{max}$ is 100.

5.1. Data sets

To test the efficiency of the proposed model and matheuristic algorithm, we generate a set of instances based on the Chitsaz et al. (2019) benchmark which is adapted from PRP instances of Archetti et al. (2011). The new instances include 6 periods and a number of nodes equal to 14 and 50. These nodes present the suppliers or warehouses. These instances keep the original horizon of production capacity, and the distances between the nodes. For the inventory limits at the plant, we chose to share it between return products, new products, and components. A dynamic demand per period is randomly generated by uniform distribution between $0.5 * D$ and $1.5 * D$ where D is the demand per period in instances of Chitsaz et al. (2019). A dynamic setup, purchase, inventory and production costs are randomly generated by uniform distribution $\pm 30\%$ of the values obtained from instances of Chitsaz et al. (2019). For each instance, we generate a number of scenarios equal to 5, 50 and 100 that represent the random yields. In each instance, we check the non-redundancy of the scenarios.

5.2. Managerial insights

In order to identify the impact of the different hypotheses explained in Section 3.3 a set of tests is performed. Tables 3 and 4 present the results and the deviations $Dev0(\%)$ between the optimal solutions obtained under the hypothesis H_0 and the other hypotheses H_x ($Dev0(\%) = \frac{sol.H_0 - sol.H_x}{sol.H_x}$) and the average (Avg) also the median (Med) of those Deviations.

We start our experimentation by comparing the results under five scenarios for 10 instances with 14 nodes. According to the results shown in Table 3, it can be observed that solving the problem with H_0 is faster than with the remaining hypotheses because there are fewer decisions that are impacted by the scenarios. Consequently, with H_0 also for H_1 and H_2 , the problem is solved to the optimal.

Comparing the results of H_0 with that of H_1 show that adding flexibility to production improves slightly the total cost ($Avg_Dev0 = 0.10\%$), where the produced quantity with H_1 remains unchanged even if it depends on the scenarios. However, the quantity to be disassembled changed. Solving the problem with H_1 allows us to find the majority of the same optimal solutions founded by H_0 (9 instances among the 10) but with a higher CPU time.

Moreover, adding flexibility to the purchased quantities with H_2 improves the results of H_0 with $Avg_Dev0 = 5.70\%$. Comparing the results of H_0 and H_3 shows a significant improvement in the total cost. This improvement can reach 22.80%. With the two hypotheses H_4 and H_3 , we find the majority of the same solutions but with different CPU times. Indeed, the resolution with H_4 is faster in most cases in comparison with H_3 .

Based on the deviation results presented in Table 4, H_1 slightly improves H_0 . Conversely, H_2 , H_3 and H_4 significantly improve H_0 . These improvements are practically equivalent ($Avg_Dev0 = 6.30\%$ and $Avg_Dev0 = 6.40\%$). In contrast, having more flexibilities in the decisions improves the total cost in each hypothesis, but the difficulty of solving the problem increases and need more CPU time. Therefore, when solving the problem with H_3 and H_4 , the majority of the instances are not solved to the optimal.

Following this observation, we can neglect H_0 and H_1 and solve more instances of different sizes with the last 3 hypotheses.

Table 3
Results for instances with 14 nodes under 5 scenarios.

| Instance | H_0 | | H_1 | | H_2 | | H_3 | | H_4 | |
|----------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| | CPU (s) | Gap (%) | CPU (s) | Gap (%) | CPU (s) | Gap (%) | CPU (s) | Gap (%) | CPU (s) | Gap (%) |
| 1 | 4 | 0.0 | 5 | 0.0 | 77 | 0.0 | 3600 | 0.2 | 3600 | 0.2 |
| 2 | 18 | 0.0 | 28 | 0.0 | 36 | 0.0 | 3600 | 0.2 | 2830 | 0.0 |
| 3 | 69 | 0.0 | 69 | 0.0 | 7 | 0.0 | 75 | 0.0 | 52 | 0.0 |
| 4 | 12 | 0.0 | 24 | 0.0 | 76 | 0.0 | 1088 | 0.0 | 546 | 0.0 |
| 5 | 90 | 0.0 | 85 | 0.0 | 136 | 0.0 | 1217 | 0.0 | 426 | 0.0 |
| 6 | 12 | 0.0 | 23 | 0.0 | 13 | 0.0 | 2017 | 0.0 | 1676 | 0.0 |
| 7 | 22 | 0.0 | 48 | 0.0 | 115 | 0.0 | 3600 | 0.5 | 3600 | 0.3 |
| 8 | 32 | 0.0 | 55 | 0.0 | 35 | 0.0 | 3600 | 0.1 | 864 | 0.0 |
| 9 | 27 | 0.0 | 32 | 0.0 | 204 | 0.0 | 3600 | 0.8 | 3600 | 0.8 |
| 10 | 55 | 0.0 | 127 | 0.0 | 191 | 0.0 | 1455 | 0.0 | 1594 | 0.0 |
| Med | 25 | 0.0 | 40 | 0.0 | 77 | 0.0 | 2809 | 0.1 | 1635 | 0.0 |
| Avg | 34 | 0.0 | 49 | 0.0 | 89 | 0.0 | 2385 | 0.2 | 1879 | 0.1 |

Table 4
Deviations of solutions for instances with 14 nodes under 5 scenarios.

| Instance | Dev0(H_0/H_1) | Dev0(H_0/H_2) | Dev0(H_0/H_3) | Dev0(H_0/H_4) |
|----------|-------------------|-------------------|-------------------|-------------------|
| 1 | 0.0 | 2.4 | 2.5 | 2.5 |
| 2 | 0.0 | 2.0 | 2.9 | 3.1 |
| 3 | 0.0 | 21.7 | 22.8 | 22.8 |
| 4 | 0.0 | 5.4 | 6.8 | 6.9 |
| 5 | 0.0 | 7.5 | 7.6 | 7.6 |
| 6 | 0.0 | 6.6 | 7.0 | 7.0 |
| 7 | 0.0 | 4.1 | 4.1 | 4.3 |
| 8 | 0.0 | 5.7 | 7.7 | 7.8 |
| 9 | 0.8 | 0.0 | 0.4 | 0.8 |
| 10 | 0.0 | 1.4 | 1.5 | 1.5 |
| Med | 0.00 | 4.75 | 5.45 | 5.60 |
| Avg | 0.10 | 5.70 | 6.30 | 6.40 |

5.3. Experimental results

In this section, the numerical results obtained from the MILP, the matheuristic algorithm as well as from the MILP&WS are explained. Note that a total of 200 instances with 14 and 50 components under 5, 50 and 100 scenarios are considered to compare the results between H_2 , H_3 and H_4 .

We summarize in Tables 5, 6, 7 and 8, the results for the H_2 , H_3 and H_4 for each group of instances (instances with 14 and 50 nodes). Tables from A.13 to A.22 in Appendix give the detailed numerical results.

In our preliminary experiments, we find that the solver cannot find optimal solutions for instances with 50 nodes under 50 scenarios after 3600 s. Thus, we warm start the MILP with the best solution given by the matheuristic approach. This technique is chosen to evaluate the quality of the matheuristic solution and improve it when possible. Using warm start helps also to reduce the solution CPU time.

In those tables, column MILP gives the best solution obtained using Cplex. Column Mat presents the best solutions of the matheuristic algorithm. Column MILP&WS presents the solutions of the MILP with an initial solution from the matheuristic algorithm. Columns CPU(s) show the computing time in seconds.

Column Gap(%) shows the gap given by CLPEX in 3600 s of computation time. Column Dev(%) presents the deviation between the best know solution from H_2 (Bks_{H_2}) and the best know solution from H_3 (Bks_{H_3}) ($Dev(\%) = \frac{Bks_{H_2} - Bks_{H_3}}{Bks_{H_3}}$). Column Dev1(%) presents the deviation between the best know solution from H_2 (Bks_{H_2}) and the best know solution from H_4 (Bks_{H_4}) ($Dev1(\%) = \frac{Bks_{H_2} - Bks_{H_4}}{Bks_{H_4}}$).

The CPU times for MILP&WS are calculated as the sum of the CPU time for finding the initial solution plus the CPU time of the resolution with MILP&WS. For all tables the minimum (Min), the maximum (Max), the average (Avg), and the median (Med) values are presented. In all tables, negative deviations values indicate an improvement provided by H_2 .

Table 5 shows the summary of the CPU time and the Gap of 20 instances with 14 nodes and 10 instances with 50 nodes under 5 scenarios.

For the instances with 14 nodes, MILP can prove optimality on all instances with H_2 . However, it can prove optimality only for 11 of the 20 instances within the time limit with a $Max_gap = 2.5\%$ and $Avg_Gap = 0.4\%$ for H_3 . For H_4 , it can prove optimality only for 13 of the 20 instances within the time limit with a $Max_gap = 1.7\%$ and $Avg_Gap = 0.3\%$.

As can be seen from Tables A.13, A.14 and A.15, the MILP&WS is capable to find 20 optimal solutions for all hypotheses. The matheuristic converge to the same results for almost of instances for the three hypotheses.

For all hypotheses, the matheuristic algorithm and the MILP&WS are more efficient than MILP. The matheuristic algorithm can find a good solution very fast with an $Avg_CPU = 20$ s for H_2 , $Avg_CPU = 64$ s for H_3 and $Avg_CPU = 59$ s for H_4 .

The results for the instances with 50 nodes state that the difficulty of resolution increases with the nodes size, for H_2 the $Avg_Gap = 40.7\%$, for H_3 the $Avg_Gap = 70.1\%$ and for H_4 the $Avg_Gap = 56.4\%$. From these instances, the Avg_Gap is tighter for H_2 than for H_3 and H_4 .

The solution obtained for H_2 by MILP&WS leads to an improvement in the gap (compared to the MILP) of 0.7% on average, and 1.5% as the maximal value of gap. For all instances, MILP&WS finds the best solutions in comparison with the other methods but with larger CPU times, which is equal to the sum of the CPU time of the matheuristic algorithm and the MILP.

To further assess the performance of the proposed methods, we executed the second round of tests on larger sized instances under 50 scenarios. For H_2 , the average gaps for the MILP and the MILP&WS obtained for 20 instances with 14 nodes under 50 scenarios are 7.4% and 0.0%, respectively. As can be seen from Table A.16, the MILP is not able to find any feasible solution for the 10 instances with 50 nodes under 50 scenarios. However, the MILP&WS can solve the 20 instances with $Avg_Gap = 3.6\%$. The results show that the matheuristic algorithm can find good solutions, which are improved by the MILP&WS. For H_3 , the MILP&WS improves the solutions found by the MILP with an $Avg_Gap = 0.1\%$ for instances with 14 nodes. The results show that the MILP has the worst performance; it is far from the optimal solution with an $Avg_Gap = 77.1\%$ for the instances with 14 nodes. In addition, it cannot find any feasible solution for instances with 50 nodes (see Table A.17), where the MILP&WS proves its efficiency with an $Avg_Gap = 3.9\%$.

For H_4 , the MILP&WS improves the solutions found by the MILP with an $Avg_Gap = 0.5\%$ for instances with 14 nodes and with an $Avg_Gap = 4\%$ for instances with 50 nodes. The results show that the MILP has the worst performance; it is far from the optimal solution with an $Avg_Gap = 73.4\%$ for the instances with 14 nodes. In addition, it cannot find any feasible solution for instances with 50 nodes (see Table A.18).

Table 5
Computational performance for instances with 14 and 50 nodes under 5 scenarios.

| | | H_2 | | | | | H_3 | | | | | H_4 | | | | |
|----|-----|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| | | MILP | | Mat | MILP&WS | | MILP | | Mat | MILP&WS | | MILP | | Mat | MILP&WS | |
| | | CPU (s) | Gap (%) | CPU (s) | CPU (s) | Gap (%) | CPU (s) | Gap (%) | CPU (s) | CPU (s) | Gap (%) | CPU (s) | Gap (%) | CPU (s) | CPU (s) | Gap (%) |
| 14 | Max | 2084 | 0.00 | 52 | 212 | 0.00 | 3600 | 2.50 | 136 | 921 | 0.00 | 3600 | 1.70 | 141 | 962 | 0.00 |
| | Min | 7 | 0.00 | 5 | 14 | 0.00 | 75 | 0.00 | 14 | 82 | 0.00 | 52 | 0.00 | 11 | 136 | 0.00 |
| | Med | 70 | 0.00 | 13 | 81 | 0.00 | 2822 | 0.00 | 59 | 406 | 0.00 | 2035 | 0.00 | 44 | 374 | 0.00 |
| | Avg | 185 | 0.00 | 20 | 96 | 0.00 | 2502 | 0.40 | 64 | 436 | 0.00 | 2143 | 0.30 | 59 | 463 | 0.00 |
| 50 | Max | 3600 | 85.30 | 951 | 4551 | 1.50 | 3600 | 99.80 | 421 | 4021 | 2.50 | 3600 | 99.20 | 1036 | 4636 | 5.70 |
| | Min | 3600 | 6.00 | 40 | 3640 | 0.20 | 3600 | 17.50 | 65 | 3665 | 0.30 | 3600 | 29.00 | 62 | 3662 | 0.80 |
| | Med | 3600 | 20.90 | 90 | 3691 | 0.80 | 3600 | 98.80 | 226 | 3826 | 1.30 | 3600 | 41.20 | 277 | 3878 | 2.30 |
| | Avg | 3600 | 40.70 | 199 | 3799 | 0.70 | 3600 | 70.10 | 230 | 3830 | 1.30 | 3600 | 56.40 | 487 | 4087 | 2.90 |

Table 6
Computational performance for instances with 14 and 50 nodes under 50 scenarios.

| | | H_2 | | | | | H_3 | | | | | H_4 | | | | |
|----|-----|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| | | MILP | | Mat | MILP&WS | | MILP | | Mat | MILP&WS | | MILP | | Mat | MILP&WS | |
| | | CPU (s) | Gap (%) | CPU (s) | CPU (s) | Gap (%) | CPU (s) | Gap (%) | CPU (s) | CPU (s) | Gap (%) | CPU (s) | Gap (%) | CPU (s) | CPU (s) | Gap (%) |
| 14 | Max | 3600 | 18.1 | 948 | 4548 | 0.4 | 3600 | 99.5 | 985 | 4585 | 0.8 | 3600 | 99.1 | 549 | 4149 | 2.5 |
| | Min | 3600 | 0.8 | 29 | 3629 | 0.0 | 3600 | 12.6 | 83 | 3683 | 0.0 | 3600 | 1.6 | 124 | 3724 | 0.0 |
| | Med | 3600 | 6.7 | 161 | 3761 | 0.0 | 3600 | 93.6 | 315 | 3915 | 0.0 | 3600 | 95.1 | 217 | 3817 | 0.3 |
| | Avg | 3600 | 7.4 | 298 | 3899 | 0.0 | 3600 | 77.1 | 459 | 4059 | 0.1 | 3600 | 73.4 | 253 | 3853 | 0.5 |
| 50 | Max | - | - | 975 | 4575 | 9.8 | - | - | 2095 | 5695 | 6.2 | - | - | 3509 | 7109 | 7.8 |
| | Min | - | - | 342 | 3942 | 0.2 | - | - | 821 | 4421 | 0.7 | - | - | 421 | 4021 | 0.7 |
| | Med | - | - | 502 | 4102 | 2.3 | - | - | 1003 | 4603 | 3.6 | - | - | 1455 | 5055 | 3.6 |
| | Avg | - | - | 629 | 4229 | 3.6 | - | - | 1181 | 4781 | 3.9 | - | - | 1616 | 5216 | 4.0 |

(-): No feasible solution is available.

Table 7
Computational performance for instances with 14 nodes under 100 scenarios.

| | | H_2 | | | | | H_3 | | | | | H_4 | | | | |
|----|-----|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| | | MILP | | Mat | MILP&WS | | MILP | | Mat | MILP&WS | | MILP | | Mat | MILP&WS | |
| | | CPU (s) | Gap (%) | CPU (s) | CPU (s) | Gap (%) | CPU (s) | Gap (%) | CPU (s) | CPU (s) | Gap (%) | CPU (s) | Gap (%) | CPU (s) | CPU (s) | Gap (%) |
| 14 | Max | 3600 | 45.9 | 975 | 4575 | 3.3 | 3600 | 99.9 | 1369 | 4969 | 6.3 | 3600 | 99.7 | 2543 | 6143 | 6.5 |
| | Min | 3600 | 0.2 | 125 | 3725 | 0.0 | 3600 | 37.0 | 145 | 3745 | 0.0 | 3600 | 66.7 | 169 | 3769 | 1.1 |
| | Med | 3600 | 9.8 | 346 | 3946 | 0.9 | 3600 | 94.8 | 698 | 4298 | 3.1 | 3600 | 99.0 | 567 | 4167 | 3.7 |
| | Avg | 3600 | 13.5 | 478 | 4078 | 1.0 | 3600 | 55.9 | 705 | 4305 | 3.1 | 3600 | 77.0 | 695 | 4300 | 3.1 |

Table 8
Deviations for instances with 14 and 50 nodes under all scenarios.

| | | 5 | | 50 | | 100 | |
|----|-----|---------|----------|---------|----------|---------|----------|
| | | Dev (%) | Dev1 (%) | Dev (%) | Dev1 (%) | Dev (%) | Dev1 (%) |
| 14 | Max | 3.20 | 3.20 | 16.2 | 17.0 | 8.8 | 15.0 |
| | Min | 0.00 | 0.00 | 0.0 | 0.6 | -3.4 | -0.9 |
| | Med | 1.20 | 1.20 | 1.4 | 3.0 | 1.4 | 7.0 |
| | Avg | 1.10 | 1.20 | 3.1 | 3.7 | 1.4 | 4.8 |
| 50 | Max | 10.90 | 12.00 | 11.6 | 14.2 | - | - |
| | Min | 0.00 | 1.10 | 0.2 | 2.3 | - | - |
| | Med | 2.60 | 3.00 | 1.8 | 4.6 | - | - |
| | Avg | 3.10 | 3.70 | 3.2 | 5.5 | - | - |

(-): No feasible solution is available.

Table 7 summarize the results for 20 instances with 14 nodes under 100 scenarios. For these 20 cases, the performance of the proposed MILP&WS is superior to that of the other methods (see Tables A.19, A.20 and A.21).

For H_2 , the average gap found by MILP ($Avg_Gap = 13.5\%$) is higher than that of MILP&WS ($Avg_Gap = 1\%$). For H_3 , the average gap found by MILP ($Avg_Gap = 55.9\%$) is higher than that of MILP&WS ($Avg_Gap = 3.1\%$). For H_4 , the improvement of MILP&WS is significant, it reduces the Gap cplex from ($Avg_Gap = 77\%$) to ($Avg_Gap = 3.1\%$).

The difficulty of solving the problem increases with 100 scenarios for the MILP with H_3 and H_4 . Therefore, in 7 and 4 out of 20 cases, the MILP cannot find a feasible solution for H_3 and H_4 , respectively. In some instances, an initial solution is not sufficient to speed up the

Table 9
Correlation between the CPU times, the Nodes, the Gap for each hypothesis.

| Correlations | | CPU | Hypotheses | Nodes | Gap |
|---------------------|------------|-------|------------|-------|-------|
| Pearson correlation | CPU | 1,000 | 0,081 | 0,986 | 0,718 |
| | Hypotheses | 0,081 | 1,000 | 0,000 | 0,264 |
| | Nodes | 0,986 | 0,000 | 1,000 | 0,686 |
| | Gap | 0,718 | 0,264 | 0,686 | 1,000 |
| P-value (1-tailed) | CPU | - | 0,223 | 0,000 | 0,000 |
| | Hypotheses | 0,223 | - | 0,500 | 0,006 |
| | Nodes | 0,000 | 0,500 | - | 0,000 |
| | Gap | 0,000 | 0,006 | 0,000 | - |

Table 10
Regression model.

| Model | R | R square | Adjusted R square | Std. Error of the estimate |
|-------|-------|----------|-------------------|----------------------------|
| 1 | 0,990 | 0,979 | 0,979 | 251,658 |

Predictors: (Constant), Gap, Hypotheses, Nodes
Dependent variable: Cpu

optimization to the respective limits, and the solver spends unnecessary time on estimation. An initial solution presents an upper limit with an objective function value close to the optimum but in many cases, it makes no difference. That is why the MILP&WS was not able to find a feasible solution for 3 instances out of the 20 instances (Table A.21).

Table 8 presents a summary on the deviations between H_2 and H_3 also between H_2 and H_4 for the different scenarios. According to these results, we notice that for 14 nodes with 5 scenarios, H_3 improves H_2

Table 11
ANOVA tests.

| | Sum of squares | df | Mean square | F | P-value |
|----------------|-------------------------|-----|------------------------|-------|---------|
| Between Groups | 28 942 957 190 581,300 | 2 | 14 471 478 595 290,600 | 6,561 | 0,002 |
| Within Groups | 586 682 532 907 323,000 | 266 | 2 205 573 431 982,420 | – | – |
| Total | 615 625 490 097 905,000 | 268 | – | – | – |

Table 12
Dunn's pairwise Post-Hoc tests.

| Methods | Mean difference | Std. Error | P-value |
|-------------|-----------------|---------------|---------|
| MILP MILPWS | 697 188,63348* | 222 009,22373 | 0,004 |
| Mat MILPWS | 109,05200 | 221 388,21769 | 1,000 |

*The mean difference is significant at the 0.05 level.

at most by 3.20% and on average 1.1%. The hypothesis H_4 improves H_2 at most by 3.20% and on average 1.2%. Concerning the results with 50 scenarios, we observe that H_3 improves at most H_2 by 16.20% and on average 3.1%, and H_4 improves at most H_2 by 17% and on average 3.7%. For the results with 100 scenarios, H_3 and H_4 improve H_2 on average by 1.4% and 4.8%, respectively. Similarly, with 50 nodes and different scenarios, the results are in line with the previous findings (Table A.22).

5.4. Results analysis and statistical tests

In the previous section, we reported the results of different resolution methods for each hypothesis. The analysis of these results allows us to draw conclusions about the assumptions and the resolution methods used. Before analyzing the impacts of different levels of flexibility, we need to reassure the reliability of the resolution methods used.

For each hypothesis, we compared the results of PLNE with the matheuristic and MILP&WS. The results show that matheuristics can find good solutions. The performance of our method is reflected in the correct selection of different steps. Even if the studied problem has different costs and capacity constraints, our iterative method can easily prove its effectiveness. It is simple to adjust to solve all the hypotheses under different scenarios size, knowing that each hypothesis has its own characteristic. The memorization process inspired by the tabu search used in our method allows us to avoid finding solutions that have already been exploited. This technique allows us to escape from local optimums to speed up the resolution. That is why our matheuristic algorithm was able to find a good solution faster than Cplex. We also implement two transportation cost approximation mechanisms schedule where we switch between them in order to diversify the search.

The matheuristics presented in this work can be adapted and applied to many variants of integrated transportation and production management problems that consider distribution as part of the decision-making process. Moreover, we can add the energy constraints in the production process by integrating the problem of selection of energy sources.

One of the main contributions of this paper is the study of the impact of different flexibility levels given to decisions related to production, transportation and procurement activities. The analyses indicate that the total cost improves with the addition of flexibility to the different decisions but with a longer resolution time. On the other hand, with some flexibility given only to decisions on quantities purchased, we can guarantee that the production and routing schedules are not impacted by the changes in scenarios. Based on this managerial study we can conclude that giving flexibility only to purchasing decisions is the fastest and easiest to implement in the industry.

The analysis of results indicate that the difficulty of solving instances increases with node size and different flexibility levels. To statistically determine if there is a relationship between CPU times,

deviation and node size for each hypothesis, a correlation analysis is applied.

Table 9 shows the results of the correlation tests. The correlation coefficients indicate that the CPU times are perfectly related in a positive linear sense with the nodes size (coefficient = 0,986) and the gap given by CPLEX (coefficient = 0,718). This point is already highlighted in the previous analyses which show that the size of the instances increases the difficulty of solving the problem. This implies a higher CPU times and a higher gap. To know how the increase of the size of the node and the gap affects the CPU times a multiple linear regression model is realized (Table 10). The coefficient of determination (R-squared = 0,979) indicates that the nodes size and the gap significantly contribute to 98% of the variability of the CPU times.

Another observation made from the analysis of results is that the matheuristic and MILP&WS have almost the same performance. To test whether the difference in performance between the proposed methods is significant, ANOVA Tests and Dunn's pairwise Post-Hoc Tests are applied. We consider instances with 5 scenarios where we get feasible solutions almost the time.

We examine the hypothesis H0 versus H1 as follows:

- H0: The methods have identical performances.
- H1: At least one method is different.

The results from the ANOVA Tests (Table 11) reject H0 with a p -value = 0.002 that is lower than the level of significance = 0.05. So at least one method is more performed from the other. Thus, we applied Dunn's pairwise Post-Hoc Tests (Table 12). The results prove that a significant difference exists between the MILP&WS and the MILP with a p -value = 0.004. However, the MILP&WS and the matheuristic have the same performances with a p -value higher than the level of significance.

6. Conclusion

In this paper, we study a dynamic disassembly assembly routing problem with returns under uncertain yields. This problem integrates simultaneous assembly and disassembly operations for the first time with vehicle routing to minimize various aggregate costs. This work allows the recovery of products at the end of their life by collecting and reusing their components. Especially, it considers the stochastic nature of yields to help managers in optimizing their supply chain network based on available yields scenarios.

Initially, we formulate the SDARP-R as a minimax mixed-integer linear programming model with a two-commodity flow formulation. Secondly, an efficient matheuristic is developed based on a variable neighborhood search algorithm and a MILP. In the first phase of the solution algorithm, a lot-sizing problem is solved with approximate routing costs. The second phase handles the dates approximate routing costs. The third phase presents a procedure to recalculate the true worst cost. The model and the matheuristic are tested on a set of instances derived from the literature and modified accordingly.

We started our experimentation by adding flexibility to the decisions considered in our problem. As a result, we found that adding flexibility in procurement, which includes the quantities purchased and routing decisions, improve the total cost. However, allowing flexibility only to purchasing decisions is most practical to the industry.

We compare the performance of the MILP with the matheuristic algorithm and the MILP&WS. According to the results, the matheuristic approach is faster than the other methods and provides good quality

Table A.13
Results for instances under 5 scenarios for H_2 .

| Nodes | Instance | MILP | | | Mat | | MILP&WS | | |
|-------|----------|------------|---------|---------|-----------|---------|-----------|---------|---------|
| | | Obj | CPU (s) | Gap (%) | Obj | CPU (s) | Obj | CPU (s) | Gap (%) |
| 14 | 1 | 15 890.09 | 77.20 | 0.0 | 15 890.09 | 8 | 15 890.09 | 82 | 0.0 |
| | 2 | 19 923.87 | 36.21 | 0.0 | 19 923.87 | 52 | 19 923.87 | 74 | 0.0 |
| | 3 | 17 218.15 | 6.70 | 0.0 | 17 218.15 | 9 | 17 218.15 | 14 | 0.0 |
| | 4 | 18 590.95 | 75.66 | 0.0 | 18 590.95 | 10 | 18 590.95 | 67 | 0.0 |
| | 5 | 14 348.89 | 135.83 | 0.0 | 14 348.89 | 9 | 14 348.89 | 161 | 0.0 |
| | 6 | 16 419.54 | 13.03 | 0.0 | 16 419.54 | 13 | 16 419.54 | 24 | 0.0 |
| | 7 | 25 596.61 | 114.74 | 0.0 | 25 596.61 | 45 | 25 596.61 | 169 | 0.0 |
| | 8 | 16 198.59 | 35.16 | 0.0 | 16 198.59 | 31 | 16 198.59 | 59 | 0.0 |
| | 9 | 24 556.68 | 204.29 | 0.0 | 24 556.68 | 17 | 24 556.68 | 173 | 0.0 |
| | 10 | 19 835.72 | 190.51 | 0.0 | 19 835.72 | 13 | 19 835.72 | 80 | 0.0 |
| | 11 | 9940.03 | 63.35 | 0.0 | 9940.03 | 6 | 9940.03 | 92 | 0.0 |
| | 12 | 14 530.81 | 178.39 | 0.0 | 14 530.81 | 28 | 14 530.81 | 212 | 0.0 |
| | 13 | 13 574.99 | 2084.08 | 0.0 | 13 574.99 | 31 | 13 574.99 | 116 | 0.0 |
| | 14 | 14 396.17 | 106.45 | 0.0 | 14 396.17 | 9 | 14 396.17 | 99 | 0.0 |
| | 15 | 16 391.04 | 204.48 | 0.0 | 16 391.04 | 40 | 16 391.04 | 115 | 0.0 |
| | 16 | 15 903.75 | 23.30 | 0.0 | 15 903.75 | 18 | 15 903.75 | 170 | 0.0 |
| | 17 | 10 690.69 | 32.26 | 0.0 | 10 690.69 | 8 | 10 690.69 | 35 | 0.0 |
| | 18 | 11 808.19 | 45.86 | 0.0 | 11 808.19 | 42 | 11 808.19 | 78 | 0.0 |
| | 19 | 15 222.69 | 20.90 | 0.0 | 15 222.69 | 5 | 15 222.69 | 25 | 0.0 |
| | 20 | 10 600.58 | 50.06 | 0.0 | 10 600.58 | 8 | 10 600.58 | 81 | 0.0 |
| 50 | 1 | 67 697.96 | 3600 | 53.7 | 31 984.11 | 304 | 31 681.17 | 3904 | 1.1 |
| | 2 | 38 262.00 | 3600 | 20.3 | 31 137.17 | 178 | 30 960.20 | 3778 | 1.5 |
| | 3 | 45 523.74 | 3600 | 16.9 | 38 098.20 | 71 | 38 070.75 | 3671 | 0.6 |
| | 4 | 42 752.64 | 3600 | 21.4 | 33 714.79 | 98 | 33 661.21 | 3698 | 0.2 |
| | 5 | 251 852.95 | 3600 | 82.6 | 43 990.34 | 951 | 43 852.06 | 4551 | 0.2 |
| | 6 | 42 021.93 | 3600 | 6.0 | 40 047.79 | 40 | 39 859.68 | 3640 | 0.9 |
| | 7 | 155 986.38 | 3600 | 82.9 | 27 029.76 | 57 | 26 904.26 | 3657 | 0.9 |
| | 8 | 51 307.91 | 3600 | 20.0 | 41 446.58 | 137 | 41 217.81 | 3737 | 0.4 |
| | 9 | 58 893.32 | 3600 | 18.2 | 49 094.89 | 83 | 48 682.31 | 3683 | 1.0 |
| | 10 | 329 672.55 | 3600 | 85.3 | 48 682.54 | 72 | 48 537.80 | 3672 | 0.4 |

Table A.14
Results for instances under 5 scenarios for H_3 .

| Nodes | Instance | MILP | | | Mat | | MILP&WS | | |
|-------|----------|---------------|---------|---------|-----------|---------|-----------|---------|---------|
| | | Obj | CPU (s) | Gap (%) | Obj | CPU (s) | Obj | CPU (s) | Gap (%) |
| 14 | 1 | 15 886.72 | 3600 | 0.2 | 15 885.04 | 21 | 15 851.07 | 832 | 0.0 |
| | 2 | 19 740.79 | 3600 | 0.2 | 19 740.79 | 18 | 19 700.85 | 136 | 0.0 |
| | 3 | 16 987.57 | 75 | 0.0 | 16 987.57 | 21 | 16 987.57 | 87 | 0.0 |
| | 4 | 18 321.36 | 1088 | 0.0 | 18 321.36 | 17 | 18 321.36 | 82 | 0.0 |
| | 5 | 14 330.78 | 1217 | 0.0 | 14 330.78 | 14 | 14 330.42 | 402 | 0.0 |
| | 6 | 16 359.54 | 2017 | 0.0 | 16 359.54 | 136 | 16 357.93 | 204 | 0.0 |
| | 7 | 25 601.59 | 3600 | 0.5 | 25 555.55 | 115 | 25 475.37 | 520 | 0.0 |
| | 8 | 15 852.70 | 3600 | 0.1 | 15 837.55 | 58 | 15 837.55 | 246 | 0.0 |
| | 9 | 24 457.25 | 3600 | 0.8 | 24 318.38 | 26 | 24 268.61 | 755 | 0.0 |
| | 10 | 19 825.86 | 1455 | 0.0 | 19 827.72 | 38 | 19 825.86 | 118 | 0.0 |
| | 11 | 9914.63 | 827 | 0.0 | 9914.63 | 78 | 9914.63 | 632 | 0.0 |
| | 12 | 14 564.27 | 3600 | 1.6 | 14 356.38 | 135 | 14 334.7 | 547 | 0.0 |
| | 13 | 13 599.92 | 3600 | 2.5 | 13 330.36 | 96 | 13 259.72 | 200 | 0.0 |
| | 14 | 14 298.02 | 3600 | 0.4 | 14 295.95 | 61 | 14 240.95 | 410 | 0.0 |
| | 15 | 16 387.27 | 3600 | 1.7 | 16 187.27 | 54 | 16 108.93 | 109 | 0.0 |
| | 16 | 15 416.78 | 1256 | 0.0 | 15 416.78 | 55 | 15 416.78 | 800 | 0.0 |
| | 17 | 10 690.69 | 2038 | 0.0 | 10 690.69 | 88 | 10 690.69 | 892 | 0.0 |
| | 18 | 11 599.33 | 3491 | 0.0 | 11 600.28 | 113 | 11 599.33 | 921 | 0.0 |
| | 19 | 15 221.18 | 2030 | 0.0 | 15 222.69 | 77 | 15 221.18 | 363 | 0.0 |
| | 20 | 10 345.74 | 2154 | 0.0 | 10 345.74 | 67 | 10 345.74 | 467 | 0.0 |
| 50 | 1 | 9 473 842.14 | 3600 | 99.7 | 31 922.27 | 330 | 30 880.27 | 3930 | 0.6 |
| | 2 | 42 969.51 | 3600 | 29.3 | 31 120.25 | 236 | 30 946.70 | 3836 | 1.8 |
| | 3 | 45 535.31 | 3600 | 17.5 | 37 719.66 | 65 | 37 700.95 | 3665 | 0.3 |
| | 4 | 42 919.54 | 3600 | 30.0 | 31 213.96 | 236 | 30 360.96 | 3836 | 1.1 |
| | 5 | 19 658 169.33 | 3600 | 99.8 | 42 643.16 | 421 | 41 423.63 | 4021 | 1.9 |
| | 6 | 4 747 777.25 | 3600 | 99.2 | 39 918.52 | 86 | 38 812.32 | 3686 | 0.6 |
| | 7 | 3 960 572.04 | 3600 | 99.3 | 26 880.29 | 136 | 26 880.29 | 3736 | 1.4 |
| | 8 | 54 826.89 | 3600 | 28.4 | 40 044.14 | 216 | 40 044.14 | 3816 | 1.9 |
| | 9 | 7 595 305.48 | 3600 | 99.4 | 48 203.29 | 154 | 47 723.29 | 3754 | 2.5 |
| | 10 | 2 802 442.90 | 3600 | 98.3 | 47 429.04 | 416 | 47 126.83 | 4016 | 0.9 |

solutions on the small and medium test instances. However, for all hypothesis, the difficulty of solving the problem increases with 14 nodes under 100 scenarios. For these instances, the matheuristic algorithm presents acceptable results but with a CPU time how reach 2543 s

because of the additional difficulty induced by capacity constraints in the assembly and disassembly model that is solved with MILP. One of the main perspectives is to develop a fast and effective heuristic for the assembly and disassembly phase. The MILP&WS is more efficient

Table A.15
Results for instances under 5 scenarios for H_4 .

| Nodes | Instance | MILP | | | Mat | | MILP&WS | | |
|-------|----------|--------------|---------|---------|-----------|---------|-----------|---------|---------|
| | | Obj | CPU (s) | Gap (%) | Obj | CPU (s) | Obj | CPU (s) | Gap (%) |
| 14 | 1 | 15 886.72 | 3600 | 0.2 | 15 851.07 | 50 | 15 851.07 | 353 | 0.0 |
| | 2 | 19 700.85 | 2830 | 0.0 | 19 700.85 | 37 | 19 700.85 | 338 | 0.0 |
| | 3 | 16 987.57 | 52 | 0.0 | 16 987.57 | 11 | 16 987.57 | 136 | 0.0 |
| | 4 | 18 301.36 | 546 | 0.0 | 18 301.12 | 20 | 18 301.12 | 267 | 0.0 |
| | 5 | 14 330.78 | 426 | 0.0 | 14 330.78 | 27 | 14 330.78 | 621 | 0.0 |
| | 6 | 16 357.93 | 1676 | 0.0 | 16 357.93 | 16 | 16 357.93 | 441 | 0.0 |
| | 7 | 25 555.55 | 3600 | 0.3 | 25 475.37 | 31 | 25 475.37 | 951 | 0.0 |
| | 8 | 15 837.55 | 864 | 0.0 | 15 837.55 | 16 | 15 837.55 | 565 | 0.0 |
| | 9 | 24 357.25 | 3600 | 0.8 | 24 157.25 | 35 | 24 157.25 | 380 | 0.0 |
| | 10 | 19 825.86 | 1594 | 0.0 | 19 825.86 | 68 | 19 825.86 | 831 | 0.0 |
| | 11 | 9914.63 | 1442 | 0.0 | 9914.63 | 54 | 9914.63 | 599 | 0.0 |
| | 12 | 14 520.12 | 3600 | 1.3 | 14 334.7 | 141 | 14 334.7 | 357 | 0.0 |
| | 13 | 13 372.58 | 3600 | 0.9 | 13 259.72 | 104 | 13 259.72 | 400 | 0.0 |
| | 14 | 14 240.95 | 2393 | 0.0 | 14 240.95 | 16 | 14 240.95 | 305 | 0.0 |
| | 15 | 16 387.27 | 3600 | 1.7 | 16 108.93 | 136 | 16 108.93 | 336 | 0.0 |
| | 16 | 15 416.78 | 702 | 0.0 | 15 416.78 | 19 | 15 416.78 | 238 | 0.0 |
| | 17 | 10 690.69 | 3099 | 0.0 | 10 690.69 | 118 | 10 690.69 | 619 | 0.0 |
| | 18 | 11 599.33 | 1131 | 0.0 | 11 599.33 | 68 | 11 599.33 | 368 | 0.0 |
| | 19 | 15 221.18 | 912 | 0.0 | 15 221.18 | 105 | 15 221.18 | 186 | 0.0 |
| | 20 | 10 420.95 | 3600 | 0.7 | 10 345.74 | 104 | 10 345.74 | 962 | 0.0 |
| 50 | 1 | 1 160 964.09 | 3600 | 97.4 | 31 176.45 | 104 | 31 016.06 | 3704 | 1.2 |
| | 2 | - | 3600 | - | 31 050.07 | 1014 | 30 623.07 | 4614 | 5.0 |
| | 3 | 62 567.11 | 3600 | 41.2 | 37 126.56 | 102 | 37 072.01 | 3702 | 0.8 |
| | 4 | 43 878.50 | 3600 | 32.7 | 30 192.58 | 242 | 30 041.98 | 3842 | 1.7 |
| | 5 | 3 021 857.05 | 3600 | 98.7 | 42 184.22 | 943 | 41 936.50 | 4543 | 4.2 |
| | 6 | 4 673 638.09 | 3600 | 99.2 | 39 146.62 | 313 | 38 440.62 | 3913 | 5.7 |
| | 7 | 36 197.70 | 3600 | 29.0 | 26 419.41 | 62 | 26 067.38 | 3662 | 1.4 |
| | 8 | 4 504 898.81 | 3600 | 99.1 | 40 011.24 | 1036 | 39 965.59 | 4636 | 2.0 |
| | 9 | 68 861.18 | 3600 | 33.3 | 48 137.93 | 945 | 48 062.04 | 4545 | 4.4 |
| | 10 | 68 927.42 | 3600 | 33.2 | 47 376.46 | 109 | 47 211.54 | 3709 | 2.5 |

(-): No feasible solution is available.

Table A.16
Results for instances under 50 scenarios for H_2 .

| Nodes | Instance | MILP | | | Mat | | MILP&WS | | |
|-------|----------|-----------|---------|---------|-----------|---------|-----------|---------|---------|
| | | Obj | CPU (s) | Gap (%) | Obj | CPU (s) | Obj | CPU (s) | Gap (%) |
| 14 | 1 | 19 981.20 | 3600 | 16.0 | 16 810.11 | 87 | 16 789.55 | 3687 | 0.0 |
| | 2 | 20 160.15 | 3600 | 1.1 | 19 958.04 | 117 | 19 947.95 | 3717 | 0.0 |
| | 3 | 19 815.76 | 3600 | 2.0 | 19 422.62 | 100 | 19 419.75 | 3700 | 0.0 |
| | 4 | 20 922.23 | 3600 | 5.7 | 19 732.99 | 278 | 19 732.39 | 3878 | 0.0 |
| | 5 | 16 651.64 | 3600 | 2.9 | 16 206.04 | 101 | 16 162.89 | 3701 | 0.0 |
| | 6 | 16 837.82 | 3600 | 1.1 | 17 016.33 | 176 | 16 648.23 | 3776 | 0.0 |
| | 7 | 28 135.71 | 3600 | 7.8 | 25 988.82 | 274 | 25 944.12 | 3874 | 0.0 |
| | 8 | 17 725.01 | 3600 | 7.9 | 16 486.59 | 41 | 16 331.32 | 3641 | 0.0 |
| | 9 | 28 173.56 | 3600 | 12.2 | 24 883.25 | 475 | 24 724.45 | 4075 | 0.0 |
| | 10 | 25 540.05 | 3600 | 18.1 | 20 925.04 | 29 | 20 919.64 | 3629 | 0.0 |
| | 11 | 13 768.58 | 3600 | 13.7 | 11 892.68 | 452 | 11 883.57 | 4052 | 0.0 |
| | 12 | 17 347.99 | 3600 | 13.5 | 15 043.23 | 667 | 15 038.14 | 4267 | 0.2 |
| | 13 | 15 580.06 | 3600 | 4.9 | 14 849.77 | 758 | 14 823.62 | 4358 | 0.0 |
| | 14 | 15 642.96 | 3600 | 7.8 | 14 503.18 | 205 | 14 427.61 | 3805 | 0.0 |
| | 15 | 20 218.13 | 3600 | 12.7 | 17 738.99 | 84 | 17 669.94 | 3684 | 0.1 |
| | 16 | 16 112.66 | 3600 | 0.8 | 15 976.35 | 948 | 15 976.63 | 4548 | 0.0 |
| | 17 | 12 666.45 | 3600 | 5.1 | 12 019.96 | 96 | 12 014.62 | 3696 | 0.0 |
| | 18 | 13 277.56 | 3600 | 3.7 | 12 786.89 | 842 | 12 786.98 | 4442 | 0.0 |
| | 19 | 17 437.40 | 3600 | 7.6 | 16 216.15 | 94 | 16 176.73 | 3694 | 0.4 |
| | 20 | 11 205.24 | 3600 | 3.6 | 10 907.54 | 146 | 10 800.43 | 3746 | 0.0 |
| 50 | 1 | - | - | - | 32 976.54 | 975 | 32 851.54 | 4575 | 4.4 |
| | 2 | - | - | - | 32 816.51 | 912 | 32 757.05 | 4512 | 1.7 |
| | 3 | - | - | - | 41 237.59 | 451 | 41 062.72 | 4051 | 1.3 |
| | 4 | - | - | - | 34 856.67 | 543 | 34 712.58 | 4143 | 2.4 |
| | 5 | - | - | - | 45 168.79 | 342 | 44 946.98 | 3942 | 1.5 |
| | 6 | - | - | - | 40 836.47 | 943 | 40 775.47 | 4543 | 2.1 |
| | 7 | - | - | - | 49 716.71 | 862 | 47 624.37 | 4462 | 6.0 |
| | 8 | - | - | - | 51 156.71 | 461 | 50 325.16 | 4061 | 9.8 |
| | 9 | - | - | - | 51 856.84 | 346 | 51 629.49 | 3946 | 6.3 |
| | 10 | - | - | - | 50 852.76 | 456 | 50 803.25 | 4056 | 0.2 |

(-): No feasible solution is available.

Table A.17
Results for instances under 50 scenarios for H_3 .

| Nodes | Instance | MILP | | | Mat | | MILP&WS | | |
|-------|----------|--------------|---------|---------|-----------|---------|-----------|---------|---------|
| | | Obj | CPU (s) | Gap (%) | Obj | CPU (s) | Obj | CPU (s) | Gap (%) |
| 14 | 1 | 70 865.29 | 3600 | 77.4 | 16 048.64 | 245 | 16 048.64 | 3845 | 0.0 |
| | 2 | 28 452.41 | 3600 | 29.9 | 19 977.91 | 342 | 19 937.21 | 3942 | 0.0 |
| | 3 | 22 095.58 | 3600 | 12.6 | 19 320.40 | 83 | 19 320.40 | 3683 | 0.0 |
| | 4 | 28 304.94 | 3600 | 31.3 | 19 444.64 | 145 | 19 444.64 | 3745 | 0.0 |
| | 5 | 66 314.95 | 3600 | 77.0 | 15 254.37 | 256 | 15 254.37 | 3856 | 0.0 |
| | 6 | 1 783 766.85 | 3600 | 99.1 | 16 646.44 | 256 | 16 646.44 | 3856 | 0.0 |
| | 7 | 1 497 790.91 | 3600 | 98.3 | 26 002.91 | 259 | 25 942.87 | 3859 | 0.8 |
| | 8 | 32 921.71 | 3600 | 51.1 | 16 114.29 | 259 | 16 114.29 | 3859 | 0.0 |
| | 9 | 1 702 665.52 | 3600 | 98.6 | 24 572.13 | 123 | 24 495.43 | 3723 | 0.1 |
| | 10 | 1 387 092.73 | 3600 | 98.5 | 20 803.57 | 562 | 20 716.75 | 4162 | 0.5 |
| | 11 | 191 392.61 | 3600 | 94.7 | 10 224.36 | 287 | 10 224.36 | 3887 | 0.0 |
| | 12 | 953 120.43 | 3600 | 98.5 | 14 667.05 | 216 | 14 667.05 | 3816 | 0.0 |
| | 13 | 887 125.25 | 3600 | 98.4 | 14 367.02 | 356 | 14 367.02 | 3956 | 0.0 |
| | 14 | 28 139.80 | 3600 | 49.2 | 14 304.21 | 945 | 14 304.21 | 4545 | 0.0 |
| | 15 | 1 687 268.28 | 3600 | 99.0 | 16 285.45 | 961 | 16 285.45 | 4561 | 0.0 |
| | 16 | 211 019.89 | 3600 | 92.5 | 15 884.45 | 923 | 15 884.45 | 4523 | 0.0 |
| | 17 | 137 249.10 | 3600 | 91.3 | 11 995.51 | 945 | 11 995.51 | 4545 | 0.0 |
| | 18 | 22 741.81 | 3600 | 47.6 | 11 921.23 | 985 | 11 921.23 | 4585 | 0.0 |
| | 19 | 864 089.85 | 3600 | 98.2 | 15 622.96 | 425 | 15 491.76 | 4025 | 0.1 |
| | 20 | 2 318 123.09 | 3600 | 99.5 | 10 518.24 | 612 | 10 518.24 | 4212 | 0.0 |
| 50 | 1 | - | - | - | 32 546.02 | 1845 | 32 201.53 | 5445 | 3.4 |
| | 2 | - | - | - | 32 469.31 | 1256 | 32 469.31 | 4856 | 5.7 |
| | 3 | - | - | - | 40 436.28 | 845 | 40 436.28 | 4445 | 2.1 |
| | 4 | - | - | - | 31 107.30 | 975 | 31 107.30 | 4575 | 3.1 |
| | 5 | - | - | - | 42 523.38 | 1024 | 42 523.38 | 4624 | 0.7 |
| | 6 | - | - | - | 40 654.88 | 983 | 40 654.88 | 4583 | 3.7 |
| | 7 | - | - | - | 46 001.11 | 2095 | 45 601.11 | 5695 | 6.2 |
| | 8 | - | - | - | 50 019.67 | 945 | 48 319.67 | 4545 | 6.1 |
| | 9 | - | - | - | 51 521.22 | 1023 | 51 521.22 | 4623 | 6.2 |
| | 10 | - | - | - | 50 774.46 | 821 | 50 094.46 | 4421 | 1.5 |

(-): No feasible solution is available.

Table A.18
Results for instances under 50 scenarios for H_4 .

| Nodes | Instance | MILP | | | Mat | | MILP&WS | | |
|-------|----------|--------------|---------|---------|-------------|---------|-------------|---------|---------|
| | | Obj | CPU (s) | Gap (%) | Obj | CPU (s) | Obj | CPU (s) | Gap (%) |
| 14 | 1 | 1 523 511.73 | 3600 | 99.0 | 16 036.79 | 213 | 15 902.38 | 3813 | 0.1 |
| | 2 | 25 825.30 | 3600 | 23.5 | 19 876.21 | 218 | 19 804.15 | 3818 | 0.2 |
| | 3 | 19 630.64 | 3600 | 1.6 | 19 319.23 | 546 | 19 306.79 | 4146 | 0.0 |
| | 4 | 28 217.27 | 3600 | 32.7 | 19 364.57 | 256 | 19 064.73 | 3856 | 0.4 |
| | 5 | 23 991.19 | 3600 | 38.0 | 15 250.46 | 216 | 15 249.42 | 3816 | 2.5 |
| | 6 | 1 484 584.59 | 3600 | 98.9 | 16 645.44 | 549 | 16 550.98 | 4149 | 0.1 |
| | 7 | 2 214 403.04 | 3600 | 98.8 | 25 808.50 | 146 | 25 670.38 | 3746 | 0.4 |
| | 8 | 151 479.71 | 3600 | 89.4 | 16 104.29 | 246 | 16 101.44 | 3846 | 0.1 |
| | 9 | 669 054.46 | 3600 | 96.4 | 24 568.04 | 145 | 24 411.28 | 3745 | 0.1 |
| | 10 | 1 453 002.07 | 3600 | 98.6 | 20 794.58 | 124 | 20 704.68 | 3724 | 1.2 |
| | 11 | 180 677.73 | 3600 | 94.4 | 10 154.78 | 543 | 10 154.78 | 4143 | 0.4 |
| | 12 | 604 089.37 | 3600 | 97.6 | 14 667.54 | 246 | 14 604.29 | 3846 | 0.4 |
| | 13 | 1 592 994.91 | 3600 | 99.1 | 14 353.71 | 126 | 14 345.52 | 3726 | 1.5 |
| | 14 | 19 963.72 | 3600 | 28.3 | 14 304.21 | 156 | 14 304.21 | 3756 | 0.0 |
| | 15 | 377 252.44 | 3600 | 95.7 | 16 285.45 | 245 | 16 285.45 | 3845 | 0.0 |
| | 16 | 194 161.11 | 3600 | 91.9 | 15 808.36 | 346 | 15 802.24 | 3946 | 0.4 |
| | 17 | 784 427.03 | 3600 | 98.5 | 11 624.74 | 246 | 11 528.35 | 3846 | 0.9 |
| | 18 | 17 710.48 | 3600 | 33.0 | 11 887.37 | 124 | 11 881.55 | 3724 | 0.2 |
| | 19 | 659 633.94 | 3600 | 97.7 | 15 606.79 | 156 | 15 469.38 | 3756 | 0.7 |
| | 20 | 23 244.64 | 3600 | 54.9 | 10 518.24 | 213 | 10 490.35 | 3813 | 0.1 |
| 50 | 1 | - | - | - | 32 109.70 | 2136 | 32 109.70 | 5736 | 3.7 |
| | 2 | - | - | - | 31 270.85 | 1346 | 31 270.85 | 4946 | 2.2 |
| | 3 | - | - | - | 39 203.20 | 421 | 38 203.84 | 4021 | 3.4 |
| | 4 | - | - | - | 31 093.32 | 1563 | 30 403.15 | 5163 | 1.4 |
| | 5 | - | - | - | 42 452.49 | 1096 | 42 449.02 | 4696 | 0.7 |
| | 6 | - | - | - | 39 453.15 | 945 | 39 453.15 | 4545 | 3.1 |
| | 7 | - | - | - | 45 960.13 | 2456 | 44 660.13 | 6056 | 4.4 |
| | 8 | - | - | - | 49 168.5974 | 3509 | 48 168.5974 | 7109 | 7.10 |
| | 9 | - | - | - | 50 179.28 | 2043 | 50 179.28 | 5643 | 7.80 |
| | 10 | - | - | - | 49 463.05 | 645 | 49 463.05 | 4245 | 6.6 |

(-): No feasible solution is available.

Table A.19
Results for instances under 100 scenarios for H_2 .

| Nodes | Instance | MILP | | | Mat | | MILP&WS | | |
|-------|----------|-----------|---------|---------|-----------|---------|-----------|---------|---------|
| | | Obj | CPU (s) | Gap (%) | Obj | CPU (s) | Obj | CPU (s) | Gap (%) |
| 14 | 1 | 32 963.61 | 3600 | 45.9 | 17 923.44 | 346 | 17 913.44 | 3946 | 0.5 |
| | 2 | 21 195.66 | 3600 | 1.7 | 20 908.39 | 245 | 20 908.39 | 3845 | 0.3 |
| | 3 | 29 653.60 | 3600 | 34.4 | 19 475.97 | 265 | 19 475.97 | 3865 | 0.1 |
| | 4 | 22 168.39 | 3600 | 10.3 | 19 977.04 | 258 | 19 977.04 | 3858 | 0.5 |
| | 5 | 26 218.75 | 3600 | 23.9 | 19 961.08 | 125 | 19 961.08 | 3725 | 0.0 |
| | 6 | 28 726.26 | 3600 | 35.1 | 18 812.61 | 345 | 18 812.61 | 3945 | 0.9 |
| | 7 | 27 076.02 | 3600 | 0.2 | 27 935.16 | 148 | 27 935.16 | 3748 | 3.3 |
| | 8 | 20 133.75 | 3600 | 11.5 | 18 099.85 | 945 | 18 099.85 | 4545 | 1.5 |
| | 9 | 26 269.65 | 3600 | 1.4 | 25 962.97 | 965 | 25 962.97 | 4565 | 0.2 |
| | 10 | 22 305.28 | 3600 | 1.1 | 22 368.54 | 245 | 22 368.54 | 3845 | 1.4 |
| | 11 | 13 871.17 | 3600 | 13.8 | 12 051.59 | 695 | 12 051.59 | 4295 | 0.8 |
| | 12 | 17 373.00 | 3600 | 3.6 | 16 939.00 | 412 | 16 839.00 | 4012 | 0.3 |
| | 13 | 16 836.11 | 3600 | 8.6 | 15 599.21 | 695 | 15 599.21 | 4295 | 1.3 |
| | 14 | 21 172.63 | 3600 | 22.4 | 16 648.25 | 258 | 16 619.25 | 3858 | 1.1 |
| | 15 | 20 872.63 | 3600 | 12.7 | 18 396.97 | 145 | 18 396.97 | 3745 | 0.9 |
| | 16 | 17 377.05 | 3600 | 4.3 | 17 033.36 | 945 | 17 033.36 | 4545 | 2.4 |
| | 17 | 14 181.41 | 3600 | 9.2 | 13 096.15 | 236 | 13 096.15 | 3836 | 1.7 |
| | 18 | 14 131.76 | 3600 | 4.4 | 13 607.31 | 645 | 13 607.31 | 4245 | 0.7 |
| | 19 | 17 548.13 | 3600 | 6.4 | 16 569.94 | 664 | 16 569.94 | 4264 | 0.9 |
| | 20 | 17 548.13 | 3600 | 19.2 | 14 356.90 | 975 | 14 256.90 | 4575 | 0.5 |

Table A.20
Results for instances under 100 scenarios for H_3 .

| Nodes | Instance | MILP | | | Mat | | MILP&WS | | |
|-------|----------|---------------|---------|---------|-----------|---------|-----------|---------|---------|
| | | Obj | CPU (s) | Gap (%) | Obj | CPU (s) | Obj | CPU (s) | Gap (%) |
| 14 | 1 | 61 688.27 | 3600 | 72.5 | 17 007.13 | 156 | 17 007.13 | 3756 | 0.3 |
| | 2 | 68 987.08 | 3600 | 69.9 | 21 065.52 | 365 | 21 065.52 | 3965 | 1.3 |
| | 3 | 30 815.67 | 3600 | 37.0 | 19 426.09 | 456 | 19 426.09 | 4056 | 0.0 |
| | 4 | 67 085.86 | 3600 | 71.0 | 19 509.90 | 145 | 19 509.90 | 3745 | 0.3 |
| | 5 | 139 632.76 | 3600 | 85.9 | 20 333.18 | 698 | 20 333.18 | 4298 | 3.3 |
| | 6 | 18 761 854.73 | 3600 | 99.9 | 18 556.09 | 385 | 18 556.09 | 3985 | 0.2 |
| | 7 | - | 3600 | - | 27 645.21 | 269 | 27 645.21 | 3869 | 4.2 |
| | 8 | 288 375.28 | 3600 | 94.1 | 17 405.98 | 1245 | 17 405.98 | 4845 | 2.8 |
| | 9 | - | 3600 | - | 26 241.73 | 1096 | 26 241.73 | 4696 | 2.8 |
| | 10 | - | 3600 | - | 22 157.82 | 698 | 22 057.82 | 4298 | 2.8 |
| | 11 | 199 062.40 | 3600 | 94.8 | 11 079.00 | 546 | 11 079.00 | 4146 | 5.8 |
| | 12 | - | 3600 | - | 16 541.64 | 875 | 16 541.64 | 4475 | 5.6 |
| | 13 | 1 195 781.71 | 3600 | 98.8 | 15 886.47 | 985 | 15 186.47 | 4585 | 3.4 |
| | 14 | 715 131.12 | 3600 | 97.7 | 16 120.98 | 746 | 16 120.98 | 4346 | 0.1 |
| | 15 | - | 3600 | - | 18 064.08 | 698 | 18 064.08 | 4298 | 4.8 |
| | 16 | 1 488 487.83 | 3600 | 98.9 | 17 414.25 | 783 | 17 414.25 | 4383 | 4.7 |
| | 17 | 1 553 425.20 | 3600 | 99.2 | 13 551.01 | 1069 | 13 551.01 | 4669 | 6.3 |
| | 18 | 1 169 954.50 | 3600 | 99.0 | 12 902.32 | 1369 | 12 902.32 | 4969 | 6.0 |
| | 19 | - | 3600 | - | 16 383.89 | 542 | 16 383.89 | 4142 | 2.4 |
| | 20 | - | 3600 | - | 14 733.95 | 975 | 14 733.95 | 4575 | 3.9 |

(-): No feasible solution is available.

in terms of solution quality but is time consuming because it calculated as the sum of the CPU time for finding the initial solution plus the CPU time of the resolution with MILP. Probably, improving the quality of the initial solution can reduce the CPU time taken by the MILP&WS.

Finally, we propose further research directions from both problem and method perspectives. In one direction, multi-type of products can be considered as a future research area. In another direction, considering other realistic parameters of the model to be stochastic such as the random customers' demands, would be another interesting area for future research. Besides, this study considers only a robust model, however, stochastic programming can be proposed. Future studies can address this issue by developing for example a two-stage stochastic programming to solve the studied problem. Except the methods used in our paper, some of the most representative computational intelligence algorithms can be used like elephant herding optimization (Li et al., 2020), Harris hawks optimization (Zhong & Li, 2022), Runge Kutta optimizer (Ahmadianfar et al., 2021).

CRedit authorship contribution statement

Sana Frifita: Methodology, Software, Validation, Formal analysis, Writing – original draft, Visualization. **Hasan Murat Afsar:** Conceptualization, Methodology, Validation, Formal analysis, Supervision. **Faical Hnaïen:** Conceptualization, Validation, Formal analysis, Supervision.

Declaration of competing interest

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

Acknowledgments

The authors gratefully acknowledge the European Union (FEDER) which funded this research.

Table A.21
Results for instances under 100 scenarios for H_4 .

| Nodes | Instance | MILP | | | Mat | | MILP&WS | | |
|-------|----------|--------------|---------|---------|-----------|---------|-----------|---------|---------|
| | | Obj | CPU (s) | Gap (%) | Obj | CPU (s) | Obj | CPU (s) | Gap (%) |
| 14 | 1 | 1 473 808.51 | 3600 | 98.9 | 16 456.11 | 546 | 16 456.11 | 4146 | 3.3 |
| | 2 | 1 107 279.01 | 3600 | 98.2 | 20 374.21 | 256 | 20 374.21 | 3856 | 2.8 |
| | 3 | – | 3600 | – | 20 334.74 | 257 | – | 3857 | – |
| | 4 | 3 721 999.09 | 3600 | 99.5 | 20 790.32 | 356 | 20 090.32 | 4056 | 5.1 |
| | 5 | 2 228 707.39 | 3600 | 99.2 | 18 578.96 | 254 | 18 578.96 | 3854 | 4.1 |
| | 6 | 6 392 087.54 | 3600 | 99.7 | 17 199.65 | 256 | 17 199.65 | 3856 | 1.4 |
| | 7 | 4 204 361.40 | 3600 | 99.4 | 28 021.55 | 259 | 28 021.55 | 3859 | 5.9 |
| | 8 | 1 268 604.69 | 3600 | 98.7 | 17 680.55 | 785 | 17 680.55 | 4385 | 4.5 |
| | 9 | 6 329 571.80 | 3600 | 99.6 | 25 243.16 | 236 | 25 243.16 | 3836 | 1.4 |
| | 10 | 5 155 764.18 | 3600 | 99.6 | 22 007.08 | 945 | 22 007.08 | 4545 | 4.5 |
| | 11 | 194 259.04 | 3600 | 94.7 | 10 479.87 | 967 | 10 479.87 | 4567 | 1.1 |
| | 12 | 4 149 682.17 | 3600 | 99.6 | 15 639.39 | 587 | 15 639.39 | 4187 | 1.4 |
| | 13 | – | 3600 | – | 15 386.09 | 326 | – | 3926 | – |
| | 14 | 657 702.72 | 3600 | 97.7 | 15 528.55 | 169 | 15 528.55 | 3769 | 3.7 |
| | 15 | 1 657 291.26 | 3600 | 99.0 | 17 023.82 | 754 | 17 023.82 | 4354 | 2.4 |
| | 16 | – | 3600 | – | 17 056.05 | 961 | – | 4561 | – |
| | 17 | 36 658.87 | 3600 | 66.7 | 13 015.87 | 2543 | 13 015.87 | 6143 | 6.2 |
| | 18 | 502 154.35 | 3600 | 97.6 | 12 360.13 | 1026 | 12 360.13 | 4626 | 3.9 |
| | 19 | – | 3600 | – | 16 723.98 | 1087 | 16 723.98 | 4687 | 6.5 |
| | 20 | 160 107.62 | 3600 | 92.5 | 12 495.52 | 1324 | 12 405.52 | 4924 | 3.1 |

(–): No feasible solution is available.

Table A.22
Different deviations for all scenarios.

| Nodes | Instance | 5 | | 50 | | 100 | |
|-------|----------|---------|----------|---------|----------|---------|----------|
| | | Dev (%) | Dev1 (%) | Dev (%) | Dev1 (%) | Dev (%) | Dev1 (%) |
| 14 | 1 | 0.25 | 0.25 | 4.62 | 5.58 | 5.06 | 8.86 |
| | 2 | 1.13 | 1.13 | 0.05 | 0.73 | –0.75 | 2.62 |
| | 3 | 1.36 | 1.36 | 0.51 | 0.59 | 0.26 | – |
| | 4 | 1.47 | 1.58 | 1.48 | 3.50 | 2.39 | –0.56 |
| | 5 | 0.13 | 0.13 | 5.96 | 5.99 | –1.83 | 7.44 |
| | 6 | 0.38 | 0.38 | 0.01 | 0.59 | 1.38 | 9.38 |
| | 7 | 0.48 | 0.48 | 0.00 | 1.07 | 1.05 | –0.31 |
| | 8 | 2.28 | 2.28 | 1.35 | 1.43 | 3.99 | 2.37 |
| | 9 | 1.19 | 1.65 | 0.93 | 1.28 | –1.06 | 2.85 |
| | 10 | 0.05 | 0.05 | 0.98 | 1.04 | 1.41 | 1.64 |
| | 11 | 0.26 | 0.26 | 16.23 | 17.02 | 8.78 | 15.00 |
| | 12 | 1.37 | 1.37 | 2.53 | 2.97 | 1.80 | 7.67 |
| | 13 | 2.38 | 2.38 | 3.18 | 3.33 | 2.72 | – |
| | 14 | 1.09 | 1.09 | 0.86 | 0.86 | 3.09 | 7.02 |
| | 15 | 1.75 | 1.75 | 8.50 | 8.50 | 1.84 | 8.07 |
| | 16 | 3.16 | 3.16 | 0.58 | 1.10 | –2.19 | – |
| | 17 | 0.00 | 0.00 | 0.16 | 4.22 | –3.36 | 0.62 |
| | 18 | 1.80 | 1.80 | 7.26 | 7.62 | 5.46 | 10.09 |
| | 19 | 0.01 | 0.01 | 4.42 | 4.57 | 1.14 | –0.92 |
| | 20 | 2.46 | 2.46 | 2.68 | 2.96 | –3.24 | 14.92 |
| 50 | 1 | 2.59 | 2.14 | 2.02 | 2.31 | – | – |
| | 2 | 0.04 | 1.10 | 0.89 | 4.75 | – | – |
| | 3 | 0.98 | 2.69 | 1.55 | 7.48 | – | – |
| | 4 | 10.87 | 12.05 | 11.59 | 14.17 | – | – |
| | 5 | 5.86 | 4.57 | 5.70 | 5.88 | – | – |
| | 6 | 2.70 | 3.69 | 0.30 | 3.35 | – | – |
| | 7 | 0.09 | 3.21 | 4.44 | 6.64 | – | – |
| | 8 | 2.93 | 3.13 | 4.15 | 4.48 | – | – |
| | 9 | 2.01 | 1.29 | 0.21 | 2.89 | – | – |
| | 10 | 2.99 | 2.81 | 1.41 | 2.71 | – | – |

(–): No feasible solution is available.

Appendix

See Tables A.13–A.22.

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