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Managing uncertain inventories, washing, and transportation of reusable containers in food retailer supply chains

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ABSTRACT

The food industry being pressured to reduce its environmental footprint, and replacing single-use packages with reusable containers would provide one such avenue for improving sustainability. The uncertainty of where and when containers are available for backhaul, insufficient washing service levels, and other barriers like intensive transportation have limited the widespread adoption of reusable containers. This paper models the tactical operations of a circular containers network with diverse actors, exploring the interdependence between uncertainty, service level, and transportation. A linear programming model is constructed where the packaging pooler's costs are minimized while meeting the demands and service needs of the food suppliers and the retailers. This model is applied to a real-world case study of a reusable container network in Italy involving the fresh food supply chain. The model is then augmented with simulations to estimate uncertain parameters and is resolved via robust optimization. We find that improving the pooler's current solution is possible, even with uncertainties of where and when containers are collected for backhaul. We quantify how improving washing service levels will change the network solution and raise costs. We likewise explore how reducing the distance suppliers must travel to collect containers impacts the pooler's operations and costs, as well as the overall distances and subsequent emissions associated with the transport of containers. While there is great potential to improve the current solution, future work is needed both to build better decision support tools and to understand of how to determine where on the Pareto frontier the solution will lie and perhaps influence it for the greater good.

1. Introduction and background

Food Supply Chains (FSCs) are responsible for over 25% of all anthropogenic GHG emissions (Poore and Nemecek, 2018). In order to meet global sustainable development goals, food companies must improve the environmental sustainability of FSCs (Campbell et al., 2018; Govindan, 2018). Consumer preferences and government regulations are increasingly pressuring businesses to reduce their environmental footprints. Circular food packaging networks represent one possibility to do so (Matthews et al., 2021; Yadav et al., 2022).

While the benefit of reducing the use of virgin plastic polymers are well-known, several barriers limit the adoption of reusable container systems (Salhoder et al., 2008; Accorsi et al., 2014; Coelho et al., 2020). The twofold diffusion and capillarity of FSC affects the cost and the management of the backhauls and washing (Gallego-Schmid et al., 2018). Reverse logistics and number of rotations are a crucial lever in designing sustainable closed-loop networks as explored by researchers (Ross and Evans, 2003; Krikke, 2011; Gonzalez et al., 2018; Cottavafava et al., 2021) or brought out by surveys (Glock, 2017; Rosa et al, 2019; Mahmoudi and Parviziomran, 2020). The diverse actors in the FSC, the suppliers, poolers, and retailers, lack the synergy to coordinate or even communicate their logistical operations. The absence of shared governance and traceability systems impairs visibility on container return flows, resulting in managerial uncertainty (Kim and Glock, 2014; Ellsworth-Krebs et al., 2022). From the perspective of the *pooler*, which manufactures, supplies, collects, and washes the containers, such uncertainty disrupts tactical and operational decisions, decreasing profitability, impacting service levels, and discouraging client participation (Otto et al., 2021; Kleine and Piscicelli, 2021). The growth and long-term sustainability of these reusable packaging networks are impeded by this uncertainty, affecting the costs, resilience, and sustainability of the

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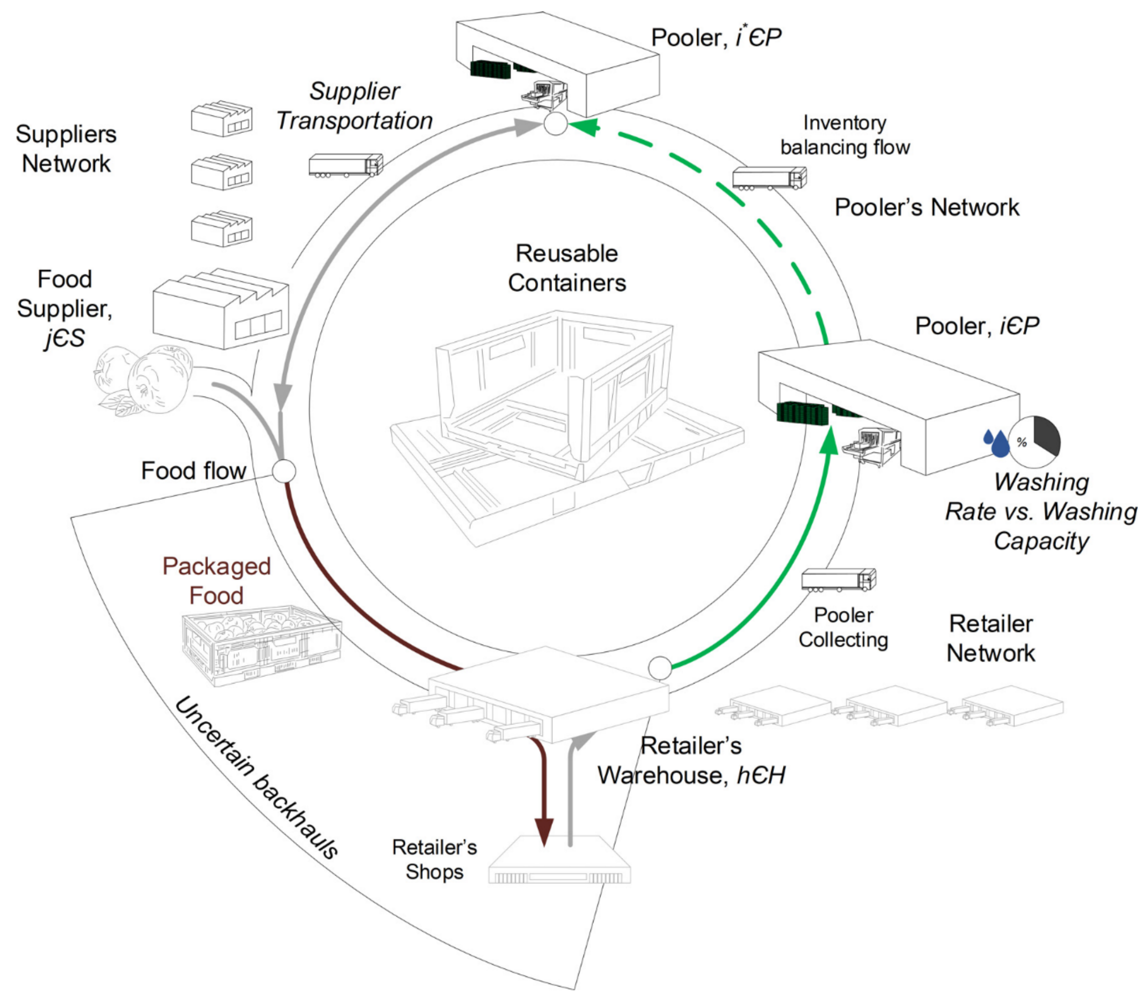

Fig. 1. Visualization of the research framework: ecosystem, entities and actors, interdependent decisional levers, uncertain backhauls, washing leverage, suppliers transportation, and RQs.

handling and distribution operations needed to meet the service level demanded by clients.

This paper explores the interplay of *uncertain backhauls and inventories* (1), *washing rate* (2), and the *transportation* (3) associated with the operations of a closed-loop network of reusable containers in the food retailer supply chains as portrayed in Fig. 1. The two levers of *uncertainty* (1) considered in this research concern both temporal (collection *lead times*) and spatial domains (*distribution rates*) across the retailers' FSC. The *lead time* is the time elapsed between the supply of empty containers to food suppliers and their backhaul from shops. It determines *when* containers become available and must be collected from a retailer's warehouse. The *distribution rat*e represents the fraction of containers sent from food suppliers to different retailers' facilities and determines from *where* the pooler collects empty containers. The temporal and spatial dimensions of uncertainty affect container inventories at the pooler's facilities and the stock balancing flow across the network. High volume and turnover necessitates continuous controlling of container inventories. Avoiding container shortages enables suppliers to relax highly constrained tactical planning problems in food harvesting and distribution operations (Ahumada et al., 2012; Mason and Villalobos, 2015). In such an integrated food-packaging supply chain, the *service level* (2) of a reusable containers system is also measured by the minimum percentage of washed containers made available to the suppliers. Washing is time- and energy-consuming but removes leftovers from containers and limits the growth of pathogens from residue. Given the food variety and the available washing capacity across the network, the pooler ensures a fraction of clean containers per rotation. However, some suppliers might require cleaning 100% of containers. Achieving such a threshold, when feasible, requires optimizing the allocation of crates to the washing lines across the pooler's facilities under weekly capacity constraints. Lastly, *transportation* (3) reflects the impact of the closed-loop network operations, the costs, and the GHG emissions from containers distribution that grow with distance traveled. The pooler must return containers from retailers and balance inventories, while the food supplier collects containers from the pooler's facilities. Therefore, reducing pooler transportation costs might increase suppliers' retrieving efforts, whereas the equilibrium between the actors' convenience is the backbone of the reusable system's sustainability. The retailers' uncertain backhauls affect container inventories, and suppliers' demanded service levels affect washing and transportation operations. In essence, the pooler is responsible for balancing and merging such interests and constraints across the circular network. This paper shows how optimization can aid the pooler in such tactical decision-making.

This research investigates the interactions among the dimensions and actors of this circular system by modeling the tactical operations of a real-world closed-loop packaging network that serves hundreds of producers and retailers in the food retailer industry. We formulate a Linear Programming (LP) decision-support model for a reusable container network to fulfill supplier demands, drive the collection and washing of crates, and avoid shortages under uncertainty. Glock and Kim (2014) introduce an inventory management model for reusable containers in a single-vendor-single-buyer supply chain. A few papers in the current literature address the tactical planning of reusable containers networks in the food industry. Soysal (2016) proposes a probabilistic Mixed-Integer Linear Programming (MILP) inventory-routing model for reusable handling items to minimize fuel consumption and transportation cost and adopts simulation to solve large instances. However, they omit essential operations, such as container washing, which are essential to closed-loop networks for food packaging. Battini et al. (2016) analyze the economic and environmental impact of reusable and disposable food containers in short and long supply chains without providing a generalizable decision-support tool to manage such systems. Bortolini et al. (2018) provide a deterministic multi-objective optimization model that identifies the optimal mix of disposable and reusable containers for a food catering chain, which is less applicable to packaging networks that use only reusable containers. Kim and Glock (2014) explore the impact of uncertain container backhauls, assuming RFID as a tracking system to reduce such uncertainty. Kim et al. (2014) further investigate how the stochastic return of Reusable Transport Items (RTIs) may lead to stockouts. Glock and Kim (2016) propose mutual inventory management strategies of products and RTIs to secure containers demand from shortage, whilst Hariga et al. (2016) suggested tailored RTIs rental strategies. Ni et al. (2015) coordinate the flows of pallets through a network made of the pallet's maker, the pooler, and multiple customers. Tornese et al. (2018) develop a simulation model to investigate two typical operational policies and tally the impact of reusable pallet handling and loading conditions and customer network structures on costs and GHG emissions. Bottani and Casella (2018) use simulation to explore the potential reduction of the environmental burden of a real-life pallet closed-loop supply chain serving a manufacturer and some retailers. In a survey of RTI-focused studies, Glock (2017) find that few papers develop tailored models from practical cases or a specific industry. They bemoan the dearth of decision-support models that optimize tactical and operational planning in multi-player reusable container systems. Liu et al. (2020) address operational decisions by optimizing the distribution flows and the vehicle-route dispatching in a third-party pooler network for RTIs. A multi-objective routing problem for collecting refillable glass bottles is solved for a real-life application in an urban scenario by Marampoutis et al. (2022). Their article considers alternative urban transport vehicles (i.e., bicycle, car, van) serving a pooler's depot from many clients. Accorsi et al. (2020) introduce a strategic network design problem tailored for a reusable food container system. MahmoumGonbadi et al. (2022) review the closed-loop supply chain design for the transition towards a circular economy, highlighting the lack of empirically-grounded research and packaging-oriented decision-support systems. This paper extends the work of Accorsi et al. (2020) by tackling the peculiar tactical issues and impacts of reusable containers networks for food products related to the mutual management of uncertain inventories and the washing and transportation processes. The paper explores balancing diverse actors' interests within a network configuration.

Fig. 1 presents the research framework and the modeled entities. The Research Questions (RQs) are framed in terms of the pooler's tactical decisions and likewise illustrated:

- *RQ1*. How does uncertain backhauls affect inventories and the tactical operations planning of the pooler's network?
- *RQ2*. How does the washing rate affect the pooler's operations and costs?
- *RQ3*. What tradeoff exists between pooler's transportation costs and the suppliers' benefits?

To address the RQs throughout this paper, we carried out a methodology based on the following steps. Section 2 presents the research material and a top-down methodology developed upon (1) a deterministic linear programming model for the food industry's closeable, washable and reusable containers. The tactical optimization model is then (2) augmented with a simulation to estimate uncertain parameters and (3) resolved via robust optimization. Section 3 applies this methodology to a case study of an Italian reusable container network for fresh produce, addressing the RQs and the pooler's practical considerations. We used multi-objective optimization for balancing the (4.1) washing rate (i.e. service level) and the (4.2) food suppliers' traveling with the pooler's interests. Section 4 interprets the results and discusses managerial ramifications. Lastly, Section 5 concludes the article by providing ideas for future work.

2. Materials, model and methodology

This research explores the interdependencies between the uncertainties affecting the tactical logistics decisions with guaranteed service levels and environmental externalities Fig. 1. illustrates the boundaries of the closed-loop network. It includes the reusable package provider or *pooler*, the *suppliers* who produce food and fill containers, and the *retailers* with their distribution chain comprised of warehouses and shops. The supplier collects containers from the pooler's plants. The pooler gathers dirty containers from a retailer's warehouse once they are returned from the shops and then carries out cleaning, storing, and eventually refurbishing, recycling, or disposal processes. However, the pooler is blind to the packaging and distribution operations performed by the suppliers and retailers. This lack of visibility generates uncertainty in terms of *where* and *when* the empty containers will be available for retrieval at retailers' warehouses, thereby affecting the pooler's tactical decision-making. The service level the pooler guarantees to the retailers is the percentage of cleaned containers provided to each supplier. The service level, together with retailers' demand and the location of their warehouses to the pooler's plants, influences collection and distribution operations (and costs) across the closed-loop network, especially as not all of the pooler's plants have washing lines. The parts of the network that the pooler directly controls are the routes that containers take to reach suppliers, the return of containers from retailers' warehouses, and any movement of containers between poolers- affect each other- shortening one set will lengthen others. Such levers are handled in this paper through a tactical time-based network model that informs the pooler's weekly decisions and then uses optimization to generate multi-scenario analyses and explore the aforementioned domains of uncertainty.

2.1. Network model

Pooler plants perform several processes: inbound storage devoted to dirty crates, washing lines cleaning dirty containers, outbound storage holding clean containers ready for shipping, and manufacturing lines recyling worn-out containers and producing new ones Fig. 2. draws the optimized containers flows. Not all facilities can perform all processes, and when the overall washing capacity is undersized (as is true in the upcoming case study) it would be infeasible to guarantee a 100% service level. The pooler's information system provides the percentage of containers collected and washed each week, the chosen time period. The time horizon $T{:}\{t_{min},\ldots,0,\ldots,t_{max}\}$ includes some setup for parameter tuning and model warm-up (i.e. $\{t_{min},\ldots,0\}$), that is followed by the tactical planning time horizon: $\{1,\ldots,t_{max}\}$. Each parameter expressed for period t refers to the status at the end of the t^{th} week. For simplicity the model assumes a single product and uniform containers. The model is formulated upon the following sets, parameters, variables, constraints, and objective function.

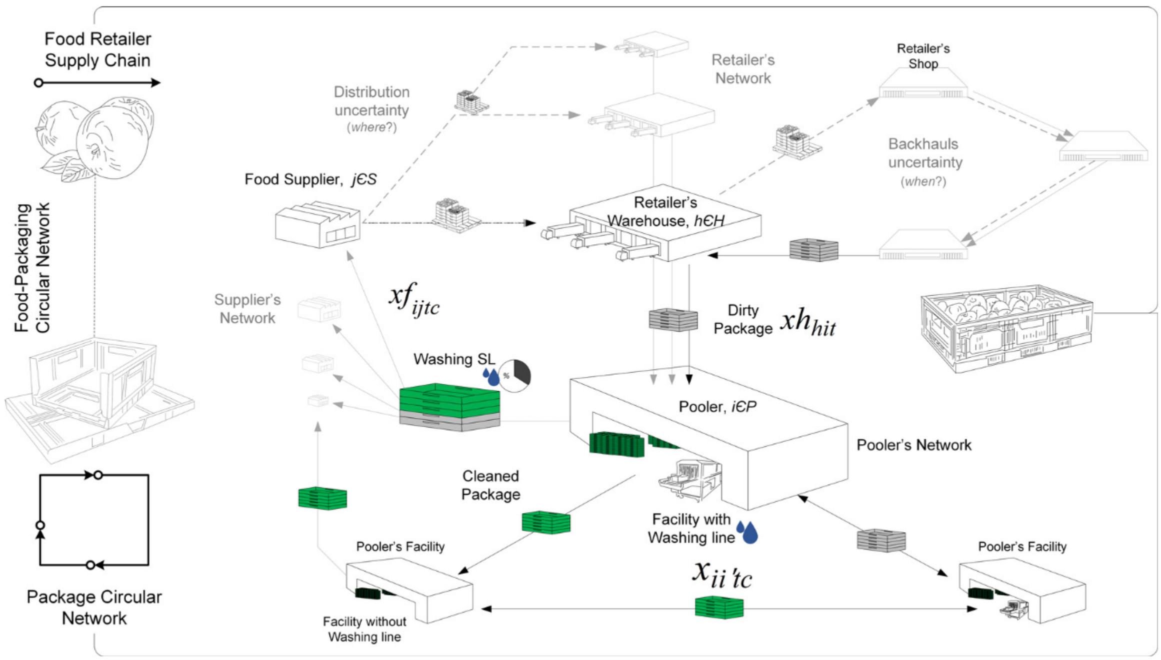

Fig. 2. Circular network flows and associated transportation decision variables

Sets

$i \in P$	Pooler plants
$j \in S$	Food suppliers
$h \in H$	Retailer warehouses
$z \in Z$	Retailer shops (used later in the uncertain backhauls estimation)
$t \in T$	Periods (i.e. a week)
$c \in C: \{d, cl\}$	State of the container (i.e. *dirty d; cleaned cl*)

Parameters

d_{jt}	Containers demanded by food supplier *j* at period *t*	[container/week]
col_{ht}	Containers to collect from retailer warehouse *h* in period $t \in T: t > 0$	[container/week]
sc_{ht}	Percentage of container inventory in plant *i* to be recycled/re-manufactured in period $t \in T: t > 0$	[%]

$$\min \sum_{i\in P}\sum_{j\in S}\sum_{t\in T:t>0}\sum_{c\in C} tc_{ij}\cdot xf_{ijtc} + \sum_{i,i'\in P}\sum_{t\in T:t>0}\sum_{c\in C} tpc_{ii'}\cdot x_{ii'tc} + \sum_{i\in P}\sum_{h\in H}\sum_{t\in T:t>0} trc_{hi}\cdot xh_{hit} + \sum_{i\in P}\sum_{t\in T:t>0} hc_i\cdot\left(Q^d_{it}+Q^{cl}_{it}\right) + \sum_{i\in P}\sum_{t\in T:t>0} clc_i\cdot xcl_{it} + \sum_{i\in P}\sum_{t\in T:t>0} pc_i\cdot(xp_{it}+ep_{it}) \quad (1)$$

Linear Constraints

$$Q^d_{it}+Q^{cl}_{it} \le cap^{hold}_i \forall\ i\in P,\ t\in T: t\ge 0 \quad (2)$$

$$Q^{cl}_{it} = Q^{cl}_{it-1}+xp_{it}+ep_{it}+xcl_{it} - \sum_{j\in S} xf_{ijtcl} + \sum_{i'\in P} x_{i'itcl} - \sum_{i'\in P} x_{ii'tcl} \forall\ i\in P,\ t\in T: t\ge 0 \quad (3)$$

$$Q^d_{it} = Q^d_{it-1}+(1-sc_{ht})\cdot\sum_{h\in H} xh_{hit} - xcl_{it} - \sum_{j\in S} xf_{ijtd} + \sum_{i'\in P} x_{i'itd} - \sum_{i'\in P} x_{ii'td} \forall\ i\in P,\ t\in T: t\ge 0 \quad (4)$$

$$xcl_{it} \le cap^{clean}_i \forall\ i\in P,\ t\in T: t\ge 0 \quad (5)$$

$$xp_{it}+ep_{it} \le cap^{prod}_i \forall i\in P,\ t\in T: t\ge 0 \quad (6)$$

$$\sum_{i\in P} xp_{it} = \sum_{i\in P}\sum_{h\in H}(1-sc_{ht})\cdot xh_{hit} \forall\ t\in T: t\ge 0 \quad (7)$$

$$\sum_{i\in P}\sum_{c\in C} xf_{ijtc} = d_{jt} \forall\ j\in S,\ t\in T: t>0 \quad (8)$$

$$\sum_{i\in P} xf_{ijtd} \le \left(1-clean^{min}_j\right)\cdot d_{jt} \forall\ j\in S,\ t\in T: t>0 \quad (9)$$

$$\sum_{i\in P} xh_{hit} = col_{ht} \forall\ h\in H,\ t\in T: t>0 \quad (10)$$

$$Q^c_{it} \ge 0 \forall\ i\in P, c\in C\ t\in T: t\ge 0 \quad (11)$$

$$xcl_{it} \ge 0 \forall\ i\in P,\ t\in T: t\ge 0 \quad (12)$$

$$xp_{it} \ge 0 \forall\ i\in P,\ t\in T: t\ge 0 \quad (13)$$

$$xf_{ijtc} \ge 0 \forall i\in P,\ \forall j\in S,\ t\in T: t>0,\ \forall c\in C \quad (14)$$

$$x_{ii'tc} \ge 0 \forall i, i'\in P,\ t\in T: t>0,\ \forall c\in C \quad (15)$$

$$xh_{hit} \ge 0 \forall i\in P,\ \forall h\in H,\ t\in T: t>0,\ \forall c\in C \quad (16)$$

The objective function (1) sums the overall operational costs experienced by the pooler. The first term $\sum_{i\in P}\sum_{j\in S}\sum_{t\in T:t>0}\sum_{c\in C} tc_{ij}\cdot xf_{ijtc}$ refers to the distribution costs of containers, either clean or dirty, from any pooler plant to the food suppliers $j \in S$. The unit cost tc_{ij} takes into account the route from origin *i* to destination *j* and scales the fixed costs of the drivers according to the container holding capacity of the truck. This cost is not affected by the state *c* of the container (i.e. dirty vs. clean) as the carrier provides the same price per pallet for both. The term

$\sum_{i,i' \in P} \sum_{t \in T:t>0} \sum_{c \in C} tpc_{ii'} \cdot x_{ii'tc}$ represents the container shipping costs between pooler's plants for any inventory rebalancing. Such movements might be significant either to better exploit holding and washing capacities, or when suppliers and retailers are concentrated in different geographic areas. For example, more food is produced in Southern Italy's favorable growing climate, while Northern Italy is more populous and has more retailer facilities. The term $\sum_{i \in P} \sum_{h \in H} \sum_{t \in T:t>0} trc_{hi} \cdot xh_{hit}$ refers to the transportation cost of containers collected from the retailers' warehouses. The term $\sum_{i \in P} \sum_{t \in T:t>0} hc_i \cdot (Q^d_{it} + Q^{cl}_{it})$ accounts for the holding costs for dirty and clean containers inventory at the pooler's plants. Lastly, the costs of washing and new container production are calculated by the terms $\sum_{i \in P} \sum_{t \in T:t>0} clc_i \cdot xcl_{it}$ and $\sum_{i \in P} \sum_{t \in T:t>0} pc_i \cdot xp_{it}$, respectively. New crates can be remanufactured from worn-out containers, and some production of extra containers (ep_{it}) will be neccessary to avoid infeasibility.

The first set of constraints (2) prevent holding capacities from being exceeded at each plant. The set of equations (3) balance the inventory of clean containers at each of the pooler's plants for each time period, and includes new production and flows received from other plants. The next set of equations (4) balance the inventory of dirty containers for each time period and plant including the return flows from the retailers' warehouses. The set of constraints (5) and (6) prevent washing and production capacities, respectively, from being exceed at each plant and for each time period. When a plant lacks either manufacturing or washing lines the parameters cap^{clean}_i and cap^{prod}_i are respectively set to zero. Equations (8) ensure the fulfillment of the overall weekly demand for containers for each food supplier from all the pooler's plants, while constraints (9) prevent the number of dirty containers delivered to each supplier from violating the established service level threshold: at least $clean^{min}_j$ percent of the containers delivered must be washed Equations (10). close the loop of this circular packaging system through the collection of containers (all dirty) from the retailers' warehouses. Constraints (11) to (16) ensure that all decision variables are non-negative.

The model supports tactical container flow planning within a given circular network. Both pooler's and retailers' facilities are already established in *Business-as-Usual* (BAU) configuration rather than according to a previously solved strategic network design problem (Accorsi et al., 2020). Flows are optimized on a weekly basis across the integrated pooler-suppliers-retailers network. Decision-making concerns container supply, collection, storage, washing, and even production operations. The production and washing capacities, cap^{prod}_i and cap^{clean}_i, are respectively tallied from the printing and cleaning lines' throughputs, while facility layout quantifies the storage capacity cap^{hold}_i given an average turnover of one week. While the number of containers is inherently integer, the large volumes of containers distributed weekly allow the tactical optimization problem to be formulated as linear with all decision variables continuous, which yields significant savings in the complexity and computational time of the solution. As a limitation, the model optimizes the flow of empty containers from/to the pooler, i.e., xf_{ijtc} and xh_{hit}, and considers the supplies of packaged food between vendors and retailers as a hidden process affecting the uncertain backhauls of containers.

2.2. Uncertain parameters estimation

Part of managing the network's uncertainity is estimating the collection *lead time* Δt_{jh}, i.e. the time when a container sent to a food supplier ($j \in S$) will become available for retrieval at a retailer's warehouse ($h \in H$). Information is available with respect to the historical orders for containers from the food suppliers and average container inventory levels at the supplier. Then, assuming the turnover of the containers at node $j \in S$ is a result of the receiving, handling, and packing/processing operations, together with the transportation phase between supplier j, the warehouse *h*, and the cycle to/from the shop $z \in Z$, a Discrete Event Simulation (DES) is set up as illustrated in Fig. 3. The model is fueled by a historical profile of receiving and shipping records for each node. It generates a sample per each lot of containers within the historical horizon of observation (12 weeks) to obtain the Probability Density Functions (PDFs) $PDF_{\Delta tjh}$, $PDF_{\Delta thz}$ or $f(\Delta t_{jh})$, $f(\Delta t_{hz})$ respectively. Given the samples per each pair $j \in S$, $h \in H$ a fitting analysis is carried assuming $\Delta t_{jh} \geq 0 \sim \text{Weibull}(\alpha, \beta)$ as shown by equations (17) and (18):

$$f(\Delta t_{jh}) = \frac{\beta}{\alpha}\left(\frac{\Delta t_{jh}}{\alpha}\right)^{\beta-1} \cdot e^{-\left(\frac{\Delta t_{jh}}{\alpha}\right)^{\beta}} \tag{17}$$

$$F\left(\Delta t_{jh}\right) = 1 - e^{-\left(\frac{\Delta t_{jh}}{\alpha}\right)^{\beta}} \tag{18}$$

The next uncertainty to be addressed is the *distribution rate*. The network model presented previously represented the number of containers to collect as fixed and used equations (10) to balance the flow of containers through the portion of the network out of the pooler's control. We will now estimate this via the general Equation (19). Here, $C \in R^{|H| \times |T|} = [c_{ht}]$, $\beta \in R^{|S| \times |H|} = [\beta_{jh}]$, and $D \in R^{|S| \times |T|} = [d_{jt-\Delta t_{jh}}]$ respectively represent the matrix of the containers received by warehouse *h* at time *t*, the weight of the arc $j\Delta h$, and the flow of containers shipped from the supplier *j* at time $t-\Delta t_{jh}$. This latter term replaces the deterministic relationship previously captured in equation (8) and references the uncertain lead time that was just estimated previously: Δt_{jh}.

$$C = \beta^T \cdot D = \begin{bmatrix} \beta_{11} & \cdots & \beta_{1S} \\ \vdots & \ddots & \vdots \\ \beta_{H1} & \cdots & \beta_{HS} \end{bmatrix} \cdot \begin{bmatrix} d_{11} & \cdots & d_{1T} \\ \vdots & \ddots & \vdots \\ d_{S1} & \cdots & d_{ST} \end{bmatrix} = \begin{bmatrix} c_{11} & \cdots & c_{1T} \\ \vdots & \ddots & \vdots \\ c_{H1} & \cdots & c_{HT} \end{bmatrix} \tag{19}$$

According to equation (19), the containers received by the warehouse *h* in time *t* results from the linear combination of the shipments of supplier *j* at time $t-\Delta t_{jh}$. The matrix multiplication formulates the uncertain flows of containers throughout the part of the supply out of the pooler's control and falls into the equivalence $c_{ht} = col_{ht}$ $\forall h \in H, t \in T$. The first step in estimating weights β_{jh} involves conducting a correlation analysis through calculating the Pearson index $\rho_{d_{jt}col_{ht}} = \frac{\sigma_{col_{ht}d_{jt-\Delta t_{jh}}}}{\sigma_{col_{ht}}\sigma_{d_{jt-\Delta t_{jh}}}}$. The Pearson index is then used to identify the most promising suppliers $j \in S^* \subset S$ to be included in the matrix β_{jh} $\forall h \in H$. Given a warehouse $h \in H$, the set $j \in S$ is ranked by decreasing value of $\rho_{d_{jt}col_{ht}}$ and the related regressor d_j added to the to subset S^*. The fitness of the iterative regression model is assessed in Fig. 4 through the indicators R^2 and $R^{2adj} = 1 - (1-R^2) \cdot \frac{|S|-1}{|S|-|D|-1}$ that penalizes regressors with a low level of correlation.

This model is refined with repect to the statistical significance of the variables, the choice of the regressors, and their multicollinearity. Such controls narrow down the set of regressors through the following two rules that are applied iteratively: (1) deleting from S^* the regressor with the highest *p-value* until all remaining variables have *p-value*≤ 0.05, and (2) removing variables with correlation $\rho_{d_{jt}col_{ht}} \geq 0.7$ and thus avoiding multicollinearity.

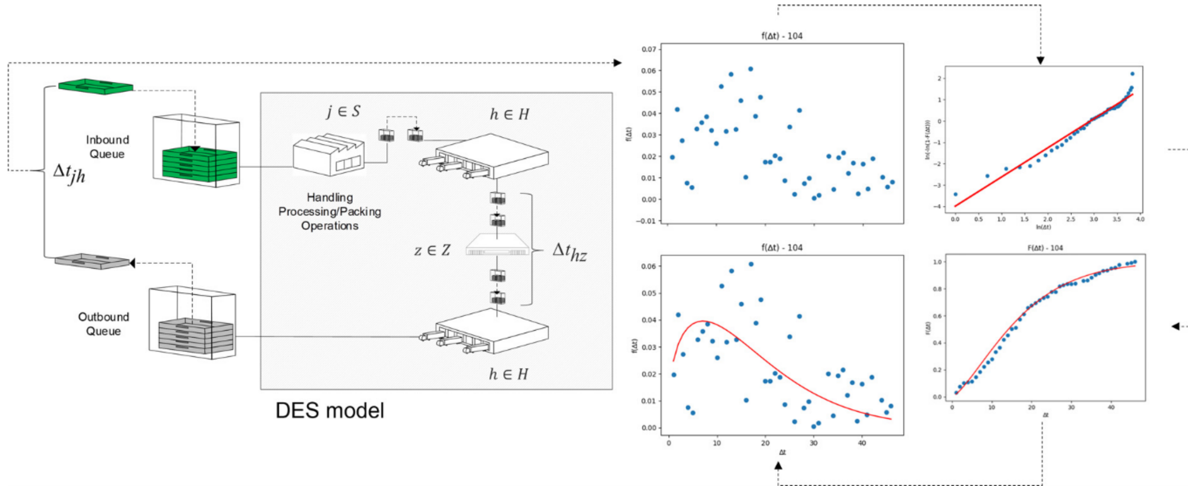

Fig. 3. DES model and fitting analysis for uncertain parameters estimation (Example of Δt_{jh} for retailer h: 104; $R^2 = 0.9627$; Mean Square Error (MSE) = 0.056).

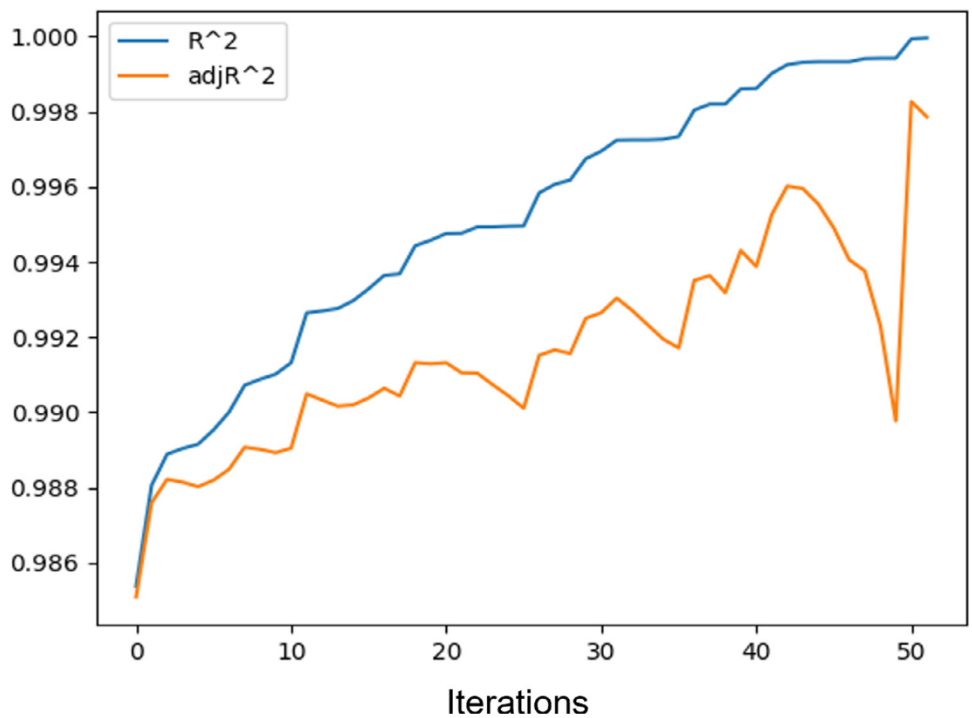

Fig. 4. Fitness of the iterative regression model (Example of retailer h: 19).

3. A retailer food supply chain case

The methodology is applied for optimizing the leading national network of reusable plastic containers (RPCs) for food items in Italy. Operating since 1998, the pooler company handles about 120 million containers per year solely for fruit and vegetable distribution, provides new containers from recycled granulated Polypropylene (PP), moves containers to and from food suppliers and retailers, and washes dirty containers. The multi-actors pooler's network is illustrated in Fig. 2 and encompasses around 900 suppliers (growers, processors, and packers) and more than 10 national retailers with their networks of warehouses and shops.

To support tactical decisions over the planning horizon of a trimester (i.e., 12 weeks), the locations of the pooler's plants are taken as fixed by assumption. The chosen time-window covers seasonal products' harvesting and consumption cycles and enables planning the container flows throughout the network until the following season. The optimization of the pooler network strategic design problem is explored in a separate study (Accorsi et al., 2020). The proposed model intended for tactical planning is propelled by an instance built upon the *as-is* scenario to fulfill the demand reported in Fig. 5. We set weekly periods to study the impacts of container backhauls on the inventories, leaving daily periods to the operational domain of future routing problem formulations. The following assumptions, pertaining only to the illustrated case study, make the model consistent with real-life constraints:

- The planning horizon of 3 months is split into 12 weekly periods $t \in T$. Containers demand d_{jt}, collection col_{ht}, and capacities parameters are scaled accordingly.
- The network includes the pooler's 20 facilities, 58 retailer warehouses, and 865 food suppliers.

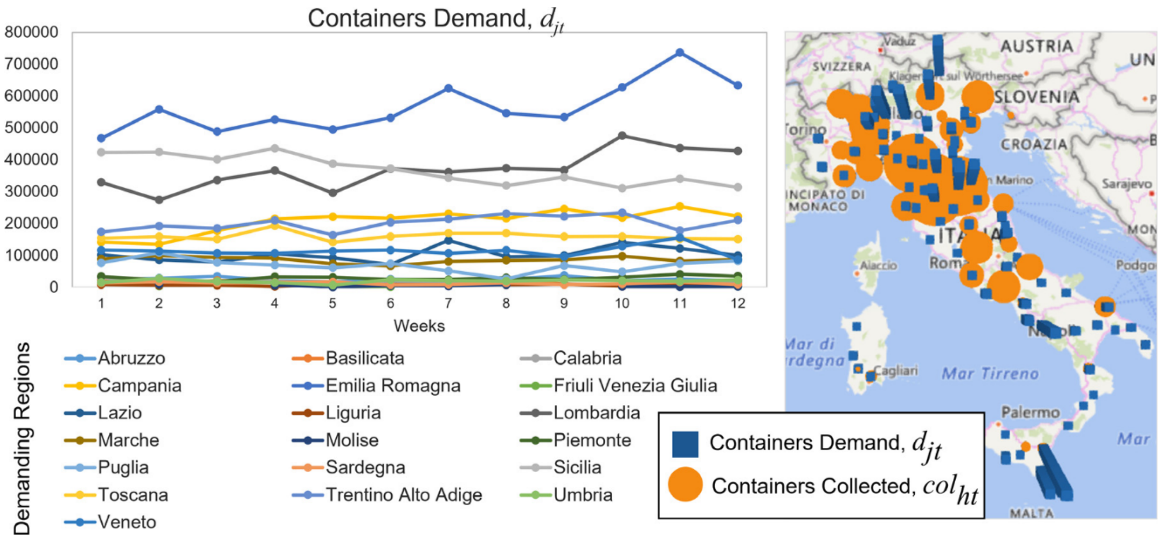

Fig. 5. Retailer food supply chain network: container demand to fulfill and location of containers to be collected

Table 1
Comparison between the as-is and optimized deterministic scenarios.

Scenario	O.F. (1) [k€/Horizon]	Manufacturing Cost [%]	Storage Cost [%]	Washing Cost [%]	Transport Cost [%]		
					Pooler-Supplier	Pooler-Pooler	Retailer-Pooler
As-Is (BAU)	2835	4	5	15	36	6	34
To-Be	2485 (-12.34%)	-	6	15	41	-	38

- Each pooler's plant ($i \in P$) is stocked at 40% of its storage capacity cap_i^{hold} with an initial inventory of dirty containers Q_{i0}^{d}. The storage cost hc_i, quantified weekly, is 0.03 [€/container].
- Based on the same instance, two scenarios are compared: *as-is (BAU)* vs. *to-be*. The flows of containers xf_{ijtc} from the plant $i \in P$ to the supplier $j \in S$ as well as the flows xh_{hit} from the retailer's warehouse $h \in H$ to the pooler $i \in P$ have been fixed for each $t \in T$ in the *as-is*, reflective of actual data for a recent 3 months of operation; Conversely, the *to-be* scenario relaxes such constraints to allow the model to determine when to deliver the containers and from which plant.
- Only four of the pooler's facilities are equipped with washing lines: two in the North (Ferrara and Pavia, named MMFE and MMPV), and two in the Center (Firenze and Latina, named MMFI and MMLT). The weekly cleaning capacity cap_i^{clean} are 546,000, 168,750, 155,250 and 90,000 respectively. The washing cost clc_i of 0.07 [€/container] is assumed to be equal for all these facilities.
- The production lines work over three 8-hours shifts, five days per week. The lines throughput is 80 containers per hour, setting the weekly production cap_i^{prod} to 9.6 thousand containers per facility. The cost of crate production pc_i is 4.55 [€/container].
- The minimum service level $clean_j^{min}$ required by all suppliers $j \in S$ is 20%, and all other parameters such as the unit costs are equalized for both scenarios.

3.1. Deterministic scenario optimization

Given these assumptions, a first tactical optimization of the pooler's network is carried out. The model is formulated in AMPL (A Mathmatical Programming Language) and solved with Gurobi through a standard dual simplex algorithm within few seconds on a computer configured with Intel® Quad Core 2.4 GHz processors and 8 GB of RAM Table 1. and Fig. 6 show the results comparing the current *BAU* and optimized *to-be* scenarios. The latter meets the containers demand from the suppliers $j \in S$ at a service level $clean_j^{min}$ without the need to either manufacture new containers or balance flows of containers between plants, and the pooler's overall costs are reduced by 12%.

The heatmaps of Fig. 6 provide a bird's eye view of the *BAU* and optimized networks where each pooler's plant counts the containers received and shipped during the planning horizon. The maps' hotspots represent the contribution of each pooler facility. After optimization, greater use of the Southern facilities reduces transportation costs Fig. 6. further highlights the flows for one facility located in Bologna (MMBO) and the other nodes serviced by it. Supplier nodes are red, retailers are yellow, and other pooler plants are green, and the direction and the intensity of the flows between these nodes is color-coded. For both scenarios MMBO collects containers from relatively close retailer warehouses, but the *as-is* scenario distributes these containers to other plants including distant ones in Sardinia and Sicily. The optimized scenario sends these containers to nearby suppliers instead.

3.2. Uncertain backhauls optimization

The results illustrated in Section 3.1 pertain to the scenario where the parameters d_{jt} and col_{ht} are assumed deterministic and known over the planning horizon, despite their uncertain nature. This formulation provides the pooler an optimal *a-posteriori* assignment of the supply, collection, washing, and storage operations among the pooler's network, and quantifies the potential cost saving from optimization. To aid tactical *a-priori* planning of such operations, a robust optimization approach is applied according to the methodology shown in Section 2.2. The uncertain collection lead time of the containers affect the inventory level forecasts at all the pooler's plants, resulting in poor visibility on the availability of dirty containers to clean, on the rebalancing flow of clean containers among the plants, and on the number of new containers to manufacture weekly to meet demand. A sensitivity analysis is performed given the following assumptions:

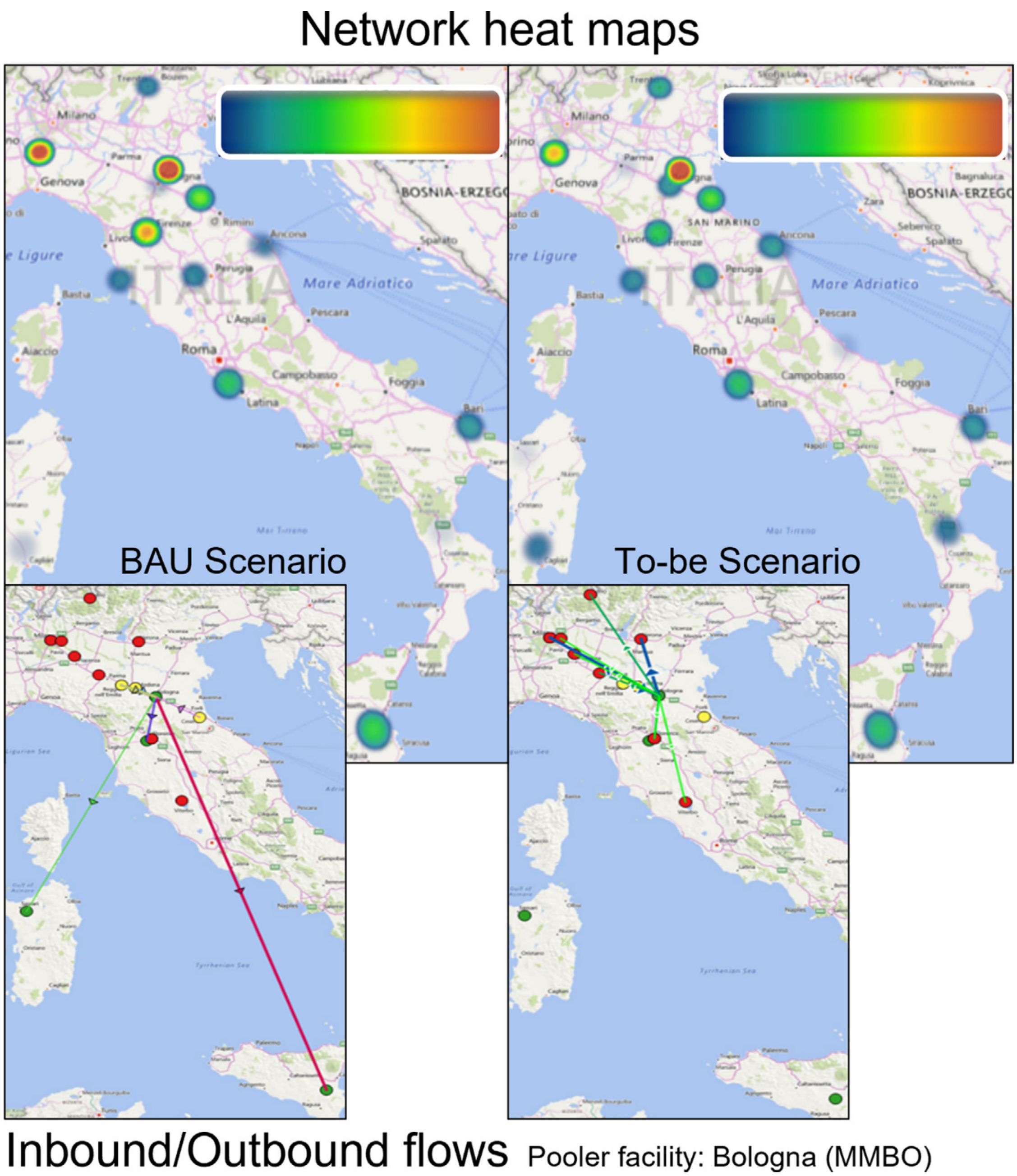

Fig. 6. Network container flows for the *BAU* scenario and optimized (to-be) deterministic scenarios; Network heat maps; Inbound/outbound flows of the pooler's facility in Bologna (MMBO).

- Every pooler's plant $i \in P$ holds an inventory of dirty containers $Q^{d}_{i0} = 0.4 \cdot Q^{c}_{i0}$ and of clean containers $Q^{cl}_{i0} = 0.6 \cdot Q^{c}_{i0}$ at period $t = 0$;
- The parameter Δt_{jh} (i.e. $\Delta t_{jh} \geq 0 \sim \text{Weibull}(\alpha, \beta)$) is stochastically generated at each iteration per every couple of $j \in S$ and $h \in H$;
- The parameters β_{jh} is calculated per each pair of $j \in S$ and $h \in H$ according to the methods from Section 2.2;
- The uncertain parameters d_{jt} and col_{ht} are defined per each $j \in S$, $h \in H$, and period $t \in T$ accordingly.

A summary of the pooler's costs resulting from 100 runs of the model is illustrated in Fig. 7. The objective function chart in the upper left shows the role of optimization for smoothing the impact of the uncertainty on the container return flows. The total pooler's costs range from less than 2300 k€/trimester, i.e. when the container return cycle from the supplier-retailer food supply chain is shorter, to more than 2800 k€/trimester in the worst case scenarios, and this cost is less than 2512 k€/trimester in half of the runs. Recalling from Table 1 that the *as-is* performance is 2835 k€/trimester, we can argue that the introduced robust optimization approach outperforms the pooler's current situation whilst accounting for the impact of uncertainty.

It is worth noting that while the storage costs are somewhat uniformly distributed over the scenarios, transportation and especially washing costs show less variability. Indeed, the stochasticity of the parameter Δt_{jh} does not greatly affect the re-manufacturing and washing costs, because the overall demand and the service level do not vary within the planning horizon. However this uncertain lead time results in greater need for re-balancing (i.e. intra-network flows) and handling/storage operations at the pooler's plants.

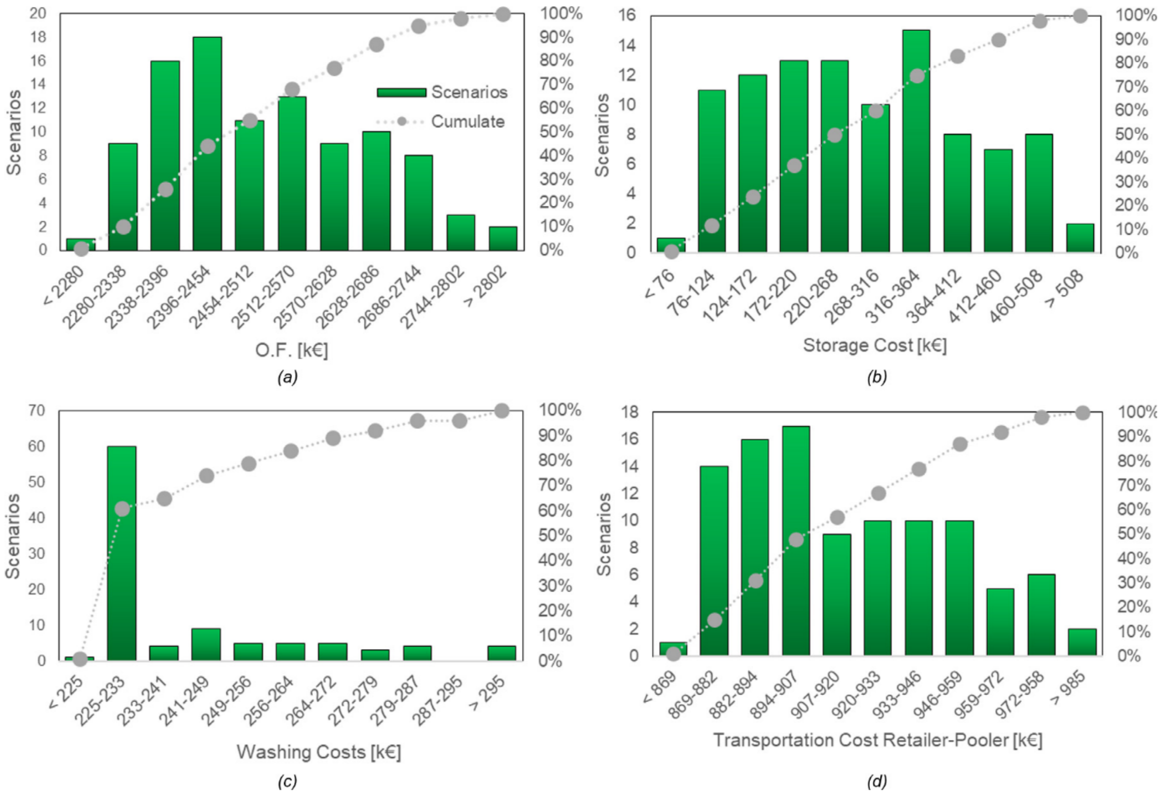

Fig. 7. Multi-scenario sensitivity analysis of the pooler's costs resulting from 100 runs of the model; Sensitivity of the objective function (OF) (*a*), of the warehousing costs (*b*), of the washing costs (*c*) and of the containers collection costs (*d*).

3.3. Washing rate sensitivity analysis

One of the pooler's targets is to increase the service level in terms of the minimum percentage of clean containers $clean_j^{min}$ sent to suppliers. It is worth noting that the parameter $clean_j^{min}$ is now aggregated for all the suppliers since the pooler uses shared storage areas for containers collected from different retailers and devoted to different suppliers. We investigate the impact on the pooler's costs by solving the bi-objective formulation of the model using the augmented ε-constrained method documented in other studies (Khalili-Damghani et al., 2012; Mavrotas, 2009). Although different approaches are used in the literature to solve multi-objective models, through the ε-constrained method we obtain an approximation of the Pareto frontier, which quantifies the trade-offs between mimimizing pooler costs and improving the average washing rate. The iterative method is implemented as follows:

Step 1. Add Constraint (20) to the problem, and set $clean_{20}^{obj} = 20\%$ at first iteration:

$$\frac{\sum_{i\in P}\sum_{j\in S}\sum_{t\in T:t>0} xf_{ijtcl}}{\sum_{j\in S}\sum_{t\in T:t>0} d_{jt}} \geq clean_k^{obj} \forall\ k : 20\ldots K\ (100\%) \tag{20}$$

Step 2. If the problem is feasible, *Solve*. Otherwise, *Stop*.

Step 3. If $k+1 \leq K$, Set $clean_{k+1}^{obj} = clean_k^{obj} + \varepsilon\ (\varepsilon = 1\%)$, $k{+}{+}$, and Go to *Step 2*. Otherwise, *Stop*.

For the case study, infeasability was reached at 75% Fig. 8. summarizes the comparison resulting from the sensitivity analysis conducted on the washing rate (i.e. service level). The left-side graph identifies the performance of each scenario in terms of the total pooler's costs. The pooler's current service level might be improved by 16% to around 36% before increasing the total cost beyond the *as-is* scenario (i.e. business-as-usual). Although the objective function (O.F.) appears to be increasing somewhat linearly, the stepwise trend for the derivative of the cost function with respect to the washing rate $\frac{\partial\ O.F.}{\partial\ clean_z^{obj}}$ can be explained as follows: once the capacity of a washing plant is fully utilized, additional dirty containers must be washed by other pooler's facilities at higher unit transport costs.

The analysis of washing capacity utilization provides insights into each pooler plant's contribution within network Fig. 9. illustrates a hierarchy of priorities among the plants which is based on a combination of their location in relation to both suppliers and retailers and their washing line capacities and costs. Such a priority could be used to drive decisions on where to invest in new or expanded washing lines to meet a target service level $clean_z^{obj}$. The plots in Figure 9 show the total containers washed at the pooler's four washing plants as the network's service level is increased, the average percentage of the clean containers supplied, and the transportation costs for each plant to supply containters. These plots indicate the thresholds of the average network service level $clean_z^{obj}$ that progressively convey flows of dirty containers toward a new pooler's plant. For instance as $clean_z^{obj}$increases the average percentage of clean containers supplied by plant MMFE drops because it is the North of Italy,and the southern suppliers can be served for lower transport costs by closer facilities.

3.4. Reusable containers transportation

Both the pooler's washing capacity $cap_i^{clean}\ \forall\ i \in P$ and the target service level affect the transport flow of containers. While the model includes the cost of this transport in the objective function (i.e. $\sum_{i\in P}\sum_{j\in S}\sum_{t\in T:t>0}\sum_{c\in C} tc_{ij}\cdot xf_{ijtc}$) to leverage the synergies of the closed-loop network, in practice the collection of containers at the plants is paid by the suppliers, not the pooler. Therefore, in reality the pooler has less incentive to reduce the logistic dis-

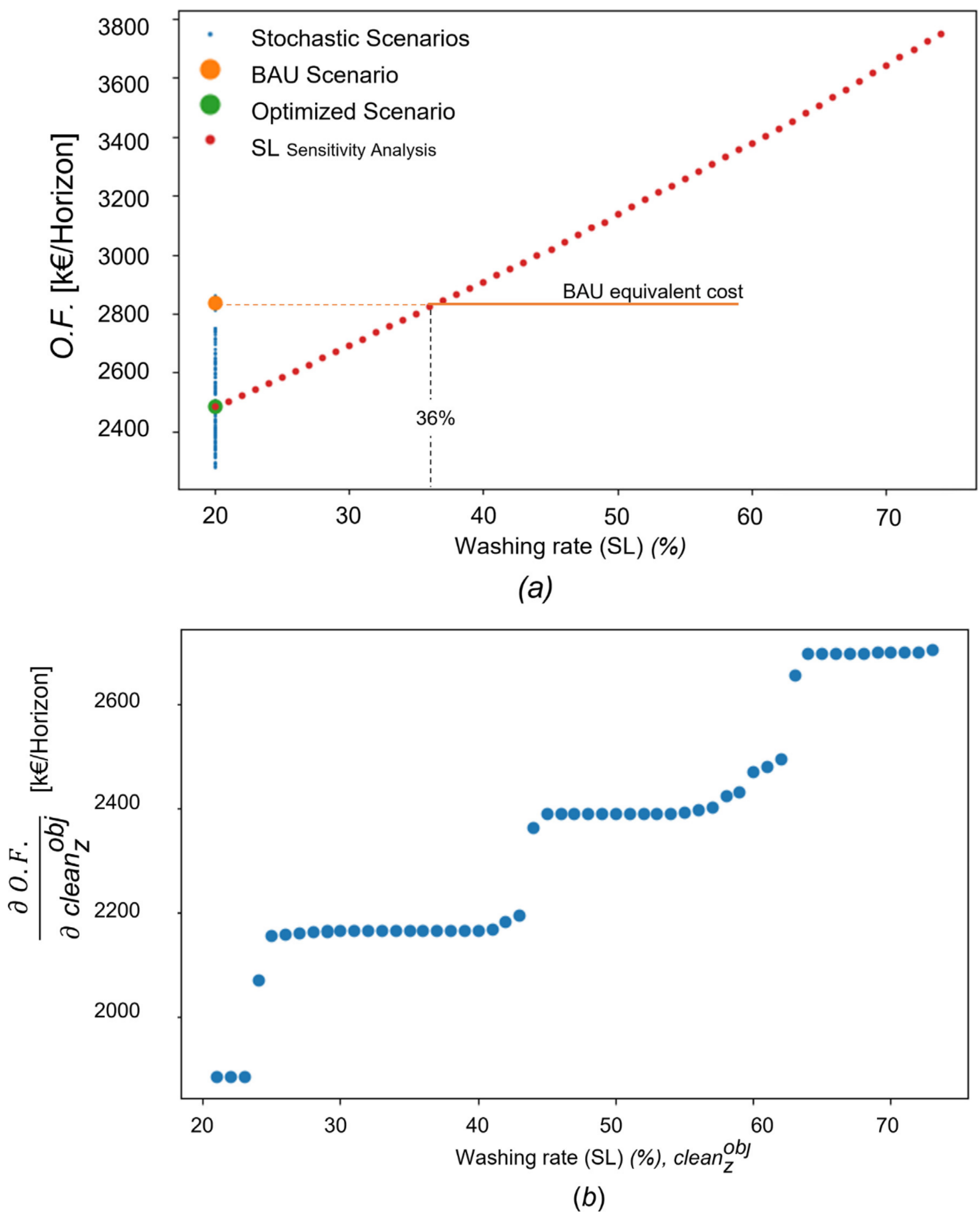

Fig. 8. Washing rate sensitivity analysis and multi-scenario comparison. Comparison of the O.F. obtained by the BAU scenario with the deterministic optimized scenario, the uncertain scenarios, and the increasing washing rate (*a*). Derivative of O.F. with respect to the washing rate (i.e. service level, SL) (*b*).

tance to the food suppliers. Nevertheless, transport distance affects the environmental impacts of the network as GHG emissions increase with the distance travelled (Xu et al., 2021). The tradeoff between keeping pooler's costs low and reducing the logistic distance d_{ij} ($\forall\ i \in P,\ j \in S$) that suppliers travel to collect containers can be quantified and assessed via a bi-objective formulation of the model using the augmented ε-constrained method previously discussed. The two objective functions are defined as follows:

$$min \sum_{i,i' \in P} \sum_{t \in T:t>0} \sum_{c \in C} tpc_{ii'} \cdot x_{ii'tc} + \sum_{i \in P} \sum_{h \in H} \sum_{t \in T:t>0} trc_{hi} \cdot xh_{hit} + \sum_{i \in P} \sum_{t \in T:t>0} hc_i \cdot \left(Q^{d}_{it} + Q^{cl}_{it}\right) + \sum_{i \in P} \sum_{t \in T:t>0} clc_i \cdot xcl_{it} + \sum_{i \in P} \sum_{t \in T:t>0} pc_i \cdot (xp_{it} + ep_{it}) \quad (21)$$

$$min \sum_{i \in P} \sum_{j \in S} \sum_{t \in T:t>0} \sum_{c \in C} d_{ij} \cdot xf_{ijtc} \quad (22)$$

The first objective function (21) considers the overall pooler's costs by now excluding the container supply service and assuming that retailers are the sole clients. In such a scenario, the retailer would use its size and bargaining power to determine

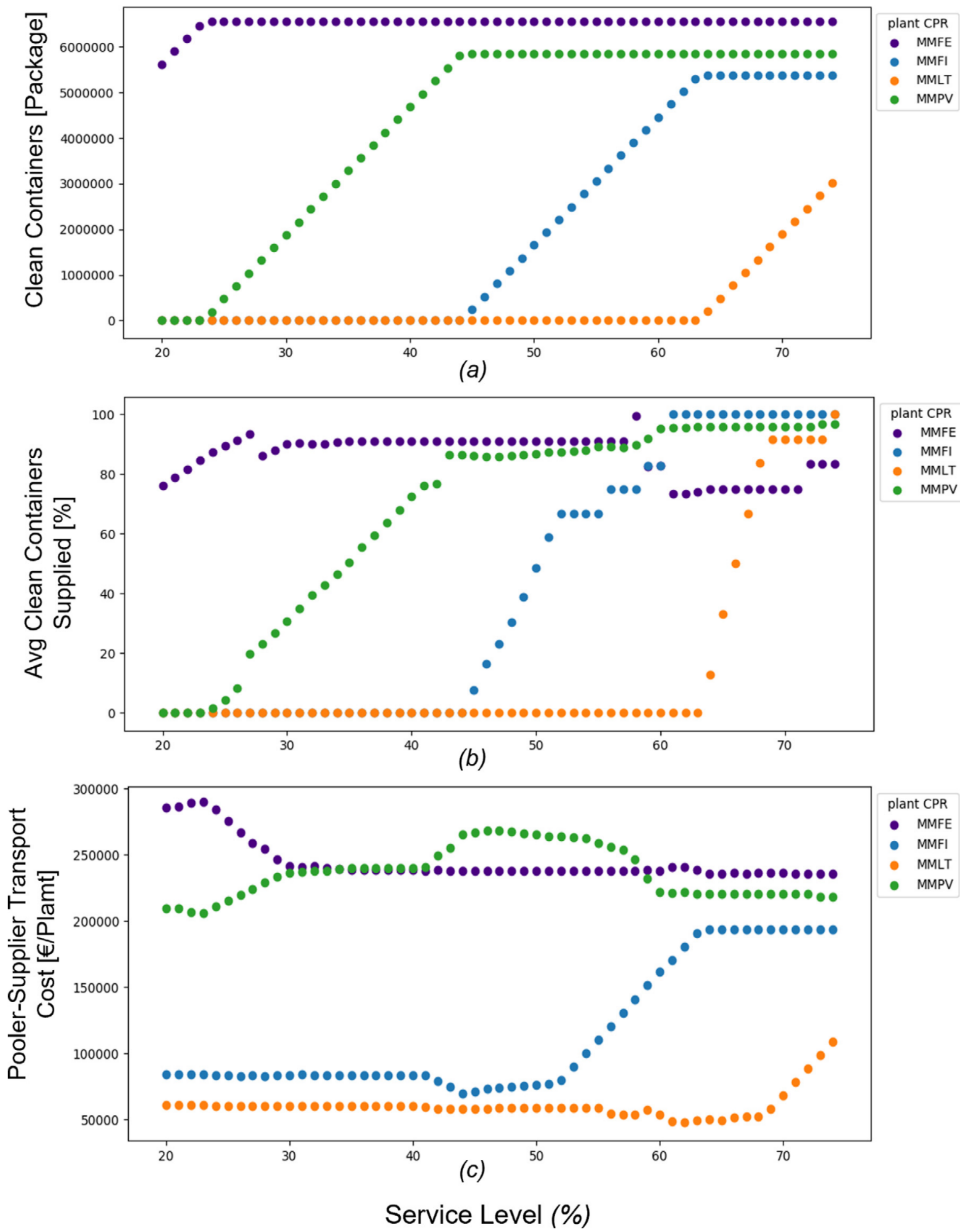

Fig. 9. Impact of the service level on washing plants and flows of clean containers. Clean containers flow per facility (*a*); Average faction of washed containers (*b*); Containers supply transport costs (*c*).

the packaging choices for the entire network and would compel suppliers to enter the pooler's network, despite the large distances involved. The second objective function (22) considers the total kilometers traveled by suppliers to collect containers from the pooler's plants. After 130 iterations, the elimination of the non-dominated solutions results in the Pareto frontier of Fig. 10, where the obtained trade-off optimal solutions can be benchmarked against the current *as-is* configuration. While the pooler's costs increase as the suppliers' average collection distance decreases, the current scenario is sub-optimal from either actors' perspectives.

Shortening the routes between the pooler's plants and the suppliers changes the logistic behavior among the network's actors Fig. 10. also shows another contribution from the optimization: the potential cost savings the pooler could experience without increasing the distances suppliers must currently travel, or conversely, how much suppliers distances (and environmental impacts) could be reduced without exceeding the current pooler's costs. The box-

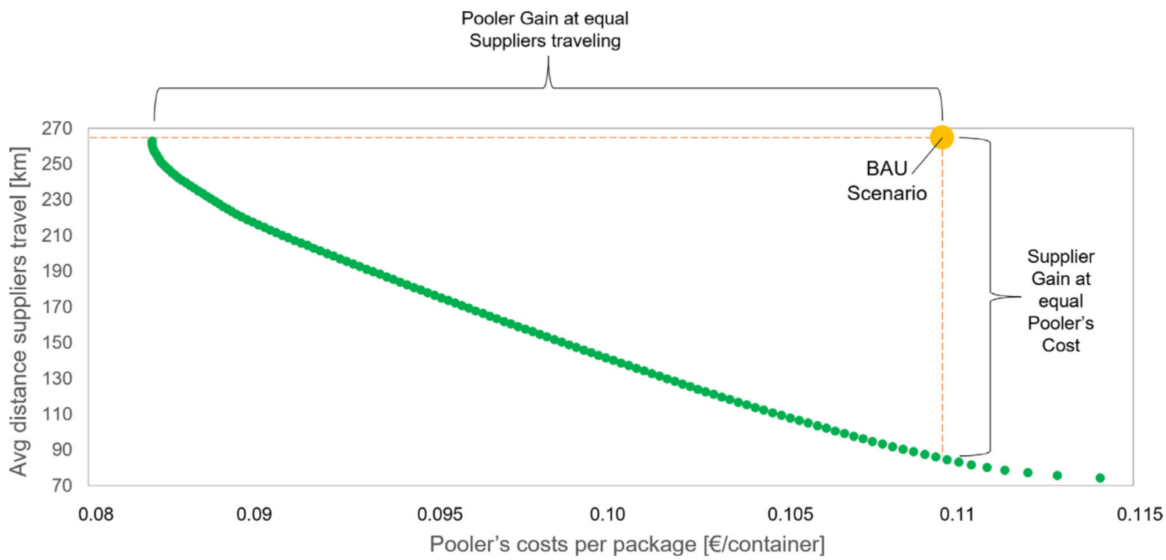

Fig. 10. Pareto frontier of the bi-objective problem formulation: pooler's costs vs. distance suppliers travel.

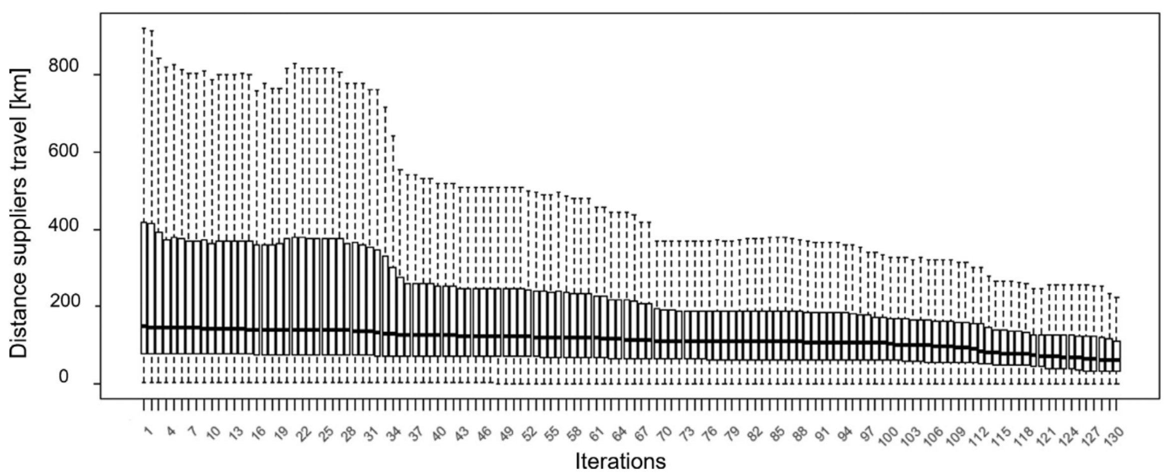

Fig. 11. Impacts of shortening suppliers routes on the network's logistic behavior: a box plot over the scenarios.

plot depicted in Fig. 11 shows that the median distance a container travels from the pooler to a supplier decreases smoothly over the iterations of the multi-objective function. Note also that the overall variability likewise drops substantially. The suppliers closest to a pooler's plant first experience slight improvements. In later iterations, the more distant suppliers benefit significantly, reducing distance traveled by up to 650 kilometers. Decreasing the distance traveled by the suppliers enhances the circular network's long-term sustainability and paves the way for success and resilience by improving the overall collective convenience of all involved actors.

However, shortening the distance that suppliers must travel has substantive tactical planning repercussions for the pooler Fig. 12. draws the flow of containers along with the traveling per each stage and actor of the circular network. It is worth noting that reducing the distance the suppliers travel forces the pooler to collect containers from more distant retailers, before using intra-network flows for rebalancing the inventories.

Fig. 12b plots the mean distance a container travels per stage of the circular network. In green, the average distance travelled from the pooler to the supplier exceeds the median shown in Fig. 11 due to the large variation in distances suppliers experience in earlier iterations. The yellow bars show that the average distances from the pooler to the retail warehouse rise slightly. Still, the most noticeable impact occurs with distances travelled between the pooler's facilities, denoted by the blue bars. After the 31th iteration, pooler-to-pooler movements become necessary due to the underlying geographical distribution of the observed network: retailers are concentrated in Northern Italy and more food is grown in Southern Italy (as shown previously in Fig. 5). It should be noted that only a subset of containers are travelling between poolers (as shown by the blue area of Fig. 12a), but when such transfers are needed, they are typically over great distances. However, the overall minimum distance travelled through the entire network occurs at the 37th iteration, showing that some plant to plant transfers will be necessary to reduce total distances traveled and the resultant GHG emissions. The *BAU* configuration is identified as a benchmark by horizontal dot lines, showing that, once again, this is a sub-optimal solution as the distances travelled by both the pooler and the suppliers could be reduced, regardless of which actors have more power.

4. Discussion and insights

Replacing single-use packages with durable plastic reusable containers would permit the food industry to improve its sustainability by simultaneously reducing extraction of virgin materials, generation of waste, and other environmental impacts (Li et al., 2015; Govindan, 2018). Despite their extraordinary potential (Battini et al., 2016; Coelho et al., 2020) and acceptance by

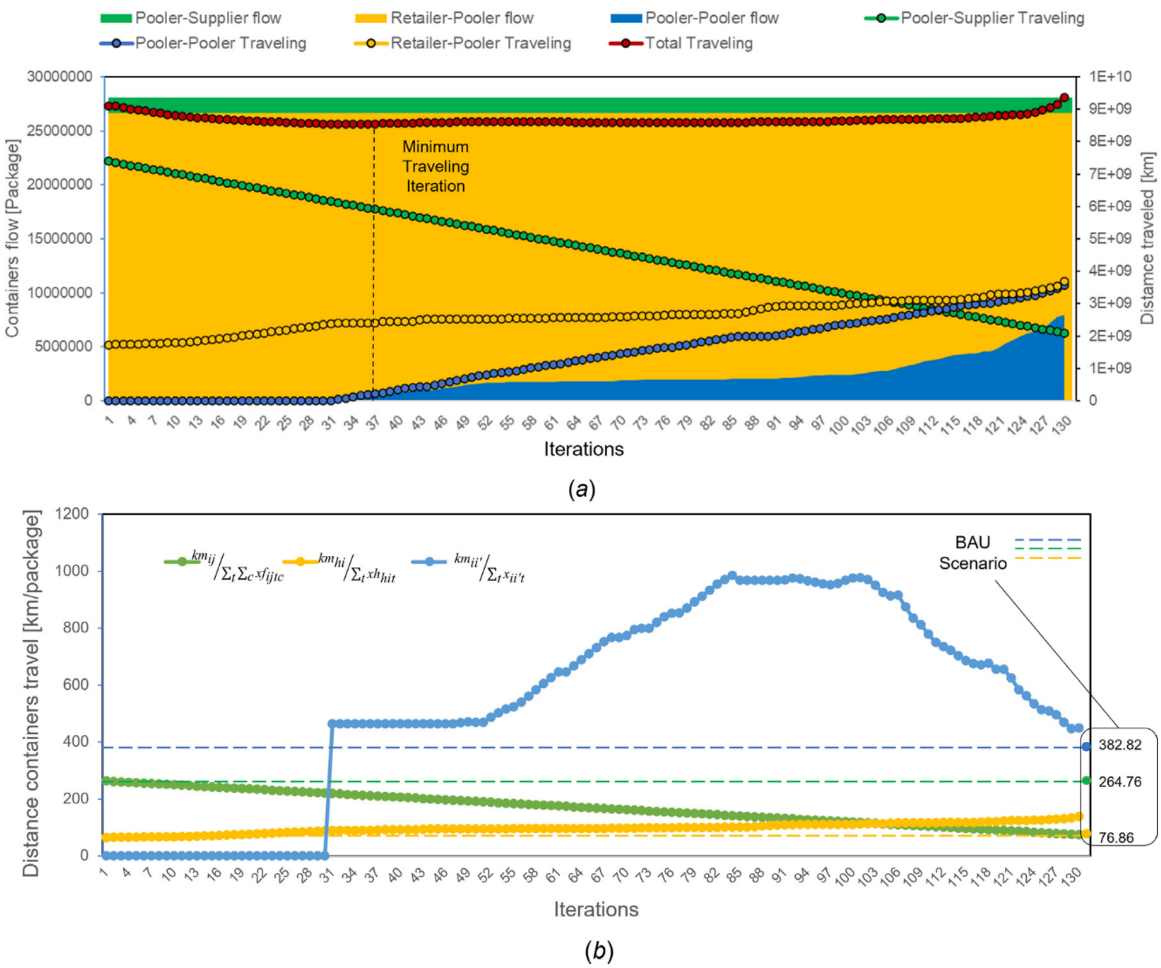

Fig. 12. Distance traveled and containers flow per stage and actor of the circular network; Sensitivity analysis shows the total minimum traveling scenario corresponding to 37th iteration (*a*); Sensitivity analysis of the mean traveling per container and stage of the circular network (*b*).

consumers (Greenwood et al., 2021), adoption of reusable containers has been slow, as suppliers and retailers alike bemoan the high service costs of reusables (Gustavo et al., 2018). Although optimization problems for reusable packaging or transport items (RTIs) are widely represented in the literature (Glock, 2017), the lack of cases studies and applied methodology represents a gap that this paper addresses. The application environment significantly affects modeling constraints and decision-making goals, and the interplay between pooler's and suppliers' needs is often neglected (as in Bortolini et al., 2018). Furthermore, real-life processes and operations characterizing the food supply chain like container washing and backhaul need to be incorporated into models, given the logistic implications these will have. This paper explores how such operational costs can be reduced and shared, even with the uncertainties that arise in tactical operations.

The solution to the deterministic model shows that the current *BAU* solution could be greatly improved through rebalancing flows through the existing network, reducing costs by over 12%, with no need for either repositioning containers between poolers or manufacturing additional containers using virgin material. The reality behind the observed circular packaging network shows that there is no omniscient, single agent in control of the containers flow, but rather that the system is populated with actors who do not pay the same costs, and their lack of coordination results in uncertainties. There is, indeed, great potential to reduce those high costs reported by Gustavo et al (2018). We thus revisit the three original research questions to address these concerns. When is a container available for return to the pooler, and where might that container be found in the network? Research question one (*RQ1*) considers how backhauls\prime temporal and spatial uncertainties affect the pooler's tactical operations and costs. Tactical operations will need to be adjusted: for example, greater lead time uncertainty results in the need for more inventory re-balancing, but transport and washing costs change little. The results from the robust optimization show that, while greater uncertainty will increase costs, all but the highest variability scenarios result in a total lower cost than the *BAU* solution. Thus, while tactical operations are affected, backhauls uncertainty in such an industrial practice is not as fiscally problematic as might have been feared.

Research Question two (*RQ2*) explores the tradeoffs associated with improving washing rate (i.e. service levels) for providing clean containers. The model finds that improvements to the service level would be possible without raising the pooler's costs much higher than the current *BAU* scenario. In the retailer case study, the pooler has insufficient washing capacity to provide high service levels. It is not surprising to discover that costs quickly increase with much higher service levels as distant facilities with available capacity must be enlisted. As the model quantifies how much improving service level will cost, such information could be used to inform where future washing capacity should be installed and determine how much such an investment would be worth. Should the pooler not benefit sufficiently from the expansion to make this investment worthwhile, subsidies could be provided. Furthermore, considering a pure practical implication, the network would be less efficient with a low washing rate as the suppliers who receive dirty containers have to bear the burden of removing residue, incurring additional costs for inspecting inbound containers to determine their cleanliness.

Research Question three (*RQ3*) goes beyond cleanliness considerations and asks the broader question how to assess the tradeoffs between pooler's costs and others' benefits, represented by suppliers' savings or environmental externalities Fig. 5. shows how the supply and demand for containers is geographically unbalanced. Shortening the suppliers' routes would compel the pooler to travel greater distances to pick up containers from retailers and, eventually, transfer some containers between plants. We showed that multi-objective optimization can quantify the trade-off between such goals. Tallying the total distance that containers must travel between the actors shows that some reduction of BAU distances would benefit both the suppliers and the pooler. The sensitivity analysis quantifies the pooler gain corresponding to equal suppliers traveling and the reduction of suppliers traveling and related GHG emissions at equal pooler's costs. Moreover, a threshold exists where the pooler will need to proactively reposition the containers via rebalancing flows. Reducing aggregate distances that containers travel (not exclusively with the pooler or the supplier's perspectives) will also improve the overall sustainability of a reusable packaging network, as it will decrease the resultant GHG emissions associated with transport.

5. Conclusion

Much work remains to be done in exploring the economics and logistics of reusable containers and making them more attractive for the food industry to adopt. Clearly, the current *as-is* scenario presented in the case study could be improved upon, but such improvement will require a decision support system that would provide the pooler's operations managers better visibility and recommendations, enabling them to make real-time tactical decisions that most cost-effectively support their service goals. Such a system would entail designing and installing a database with graphical interfaces and building user-friendly solving tools.

While they may coexist in the same network, suppliers, poolers, and retailers are all autonomous actors with separate responsibilities for their tactical operations and resultant costs. Even if the Pareto frontier can be reached with proper decision support tools, market power and other dynamics will determine just where on this frontier this solution will settle. This consideration is especially important when the greater society would benefit from a solution that incurs more direct cost for the pooler, such as reducing the total distance by containers through all parts of the network. Thus, exploration of these relationships and how they can be adjusted, such as through government regulations or subsidies (Sundqvist-Andberg and Akerman, 2021) would be worthwhile.

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.

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