A three-objective optimization model for mid-term sustainable supply chain network design

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Abstract

Supply chain network design (SCND) is a pillar of supply chain management (SCM). The modern industrial and market context, characterized by instability and dynamism, asks the supply chains and logistic networks to be designed from an integrated and reactive perspective, addressing multiple goals. Economic and environmental sustainability is the most explored target by the literature. Besides this goal, the recent mass customization paradigm, led by Industry 4.0, resulted in a significant growth of product variants, which cannot be managed by traditional production strategies, as Make-to-Stock (MTS), because of the high rising costs. Hence, stock minimization, which is one of the main pillars of the lean production philosophy, is a key competitive asset to consider in SCND. However, the current literature still lacks of integrated three-objective models simultaneously optimizing stock, economic and environmental issues in designing and managing modern supply chain networks. To fill this gap, this paper proposes and applies a mid-term three-objective linear programming optimization model to minimize, simultaneously, the stock level (lean waste), the environmental emissions (green waste), and the global supply chain network costs, getting the Pareto frontier and supporting the industrial practitioners and the logistic managers in the network design and management. A European instance exemplifies the model application getting stock, environmental and economic optima together with reasonable best-balance configurations. Among the Pareto points, the selected configuration allows reducing the stock level without a relevant increase of the environmental emissions (+1.62%) and of the supply chain network costs (+0.21%), respect to their single-objective optima.

Keywords: Supply chain network design; Environmental sustainability; Lean thinking; Stock efficiency; Multi-objective optimization; Industry 4.0.

1. Introduction

A reactive and integrated supply chain is a crucial asset enabling companies to be competitive in the modern dynamic market arena (Liang, 2008; Pishvaee and Razmi, 2012; Nasiri et al., 2014). Besides the traditional focus on optimizing costs, a relevant element to consider in supply chain management (SCM) is about the environmental sustainability of the industrial activities, which led, recently, both governments and customers to press on industrial companies to reduce the environmental impact of their processes (Ilgin et al., 2010; Amirtaheri et al., 2017; Manupati et al., 2019). The structure of the supply chain network is a strategic issue of SCM, i.e., the network of suppliers, production and distribution centres and the channels among them and the customers to get raw materials, to manufacture finished products and to distribute them to customers (Pishvaee et al., 2009; Martins et al., 2021). The supply chain network design (SCND), setting the location, number and capacities of the network facilities and the material flows among them, plays a key role in global economic and environmental sustainability performances of a supply chain (Melo et al., 2009). Furthermore, modern companies operate in the dynamic and unstable setting governed by Industry 4.0, i.e., the fourth industrial revolution. Manufacturing industries face a top level of product innovation and dynamic customer demand, leading them to embrace the mass customization paradigm to meet customers' request, satisfying the demand of a great number of product variants (Shou et al., 2017; Bortolini et al., 2018; Galizia et al., 2020). Traditional Make-to-Order (MTO) and Make-to-Stock (MTS) strategies present limits, i.e., MTO reduces storage cost but customer lead times rise up, while MTS meets customer request in a short time but the wide marketing mix makes such a strategy not often economically sustainable (Mourtzis et al., 2018). Stock minimization, which is one of the main pillars promoted by the lean production philosophy, is a further key competitive asset to consider in SCND. However, the literature still lacks of integrated three-objective approaches simultaneously optimizing stock, economic and environmental issues in designing and managing modern supply chain networks. To fill this gap, this study aims at increasing the base of quantitative studies in the field of SCM addressing the SCND, proposing and applying a three-objective linear programming optimization model to minimize stock levels along the supply chain, i.e., lean waste, environmental emissions, i.e., green waste, and the global costs generated by production, storage and distribution of products. The stock level reduction allows reaching high warehouse efficiency, while the minimization of the environmental emissions heightens the environmental sustainability of the network. In this study, following a widespread and

recognized research stream (Wang et al., 2011; Moldan et al., 2012; Little et al., 2016; Wang et al., 2020), the sustainability concept matches the environmental goals, with the aim to minimize the negative impacts on the environment. In nutshell, the novelty of this paper is to propose a new aspect, integrating lean, economic, and environmental goals in the SCND problem, as a novel issue never explored so far by the literature, as well as a new construct defining a three-objective optimization formulation to model this integration.

The literature identifies three levels of decision in SCM, i.e., strategic, tactical and operational. In this study, the tactical level of decision is focused. This level refers to mid-term decisions, multi-period modelling and multi-echelon distribution systems. The aim is to set the best system configuration and to best manage the fulfilment activities over time (Manzini, 2012; Manzini et al., 2014; Bo et al., 2021). Falling in this decisional level, the proposed model assigns suppliers to the final customers matching the production capacity to the demand trend, selecting the most appropriate shipping modes to minimize the three objective functions, i.e., stock level, environmental emissions and production, storage and distribution costs. The Pareto frontier coming from the model solving supports managers and industrial practitioners in the selection and implementation of the final supply chain network configuration.

According to the introduced goals, the remainder of this paper is organized as follows: Section 2 reviews some relevant literature on the topic. Section 3 introduces and describes the design model for a reference three-level two-stage network, while Section 4 applies the model to a European network discussing the main results and outcomes. Finally, Section 5 concludes this paper with final remarks and future research opportunities.

2. Literature review

The interest in designing sustainable supply chains is a hot topic in the recent literature (Hassini et al., 2012; Eskandarpour et al., 2015; Govindan et al., 2017; Bortolini et al., 2018; Bortolini et al., 2019; Moreno-Camacho et al., 2019). The most of the existing studies faces the topic defining and solving single- or multi-objective optimization design models (Neto et al., 2008; Rafiei et al., 2018; Kumar et al., 2020). In the field of single-objective models, Pishvaee et al. (2009) proposed a deterministic mixed-integer linear programming model for single product, single period, multi-stage logistic network design to reduce the global cost. To get a robust logistic network, the Authors developed a stochastic optimization model, considering the demand quantity, the quality of returns and the variable costs as uncertain parameters. Nagurney (2010) defined a

framework for SCND supporting the setting of the optimal levels of production and storage capacity and of the flows linked to supply chain activities, i.e., production, storage and distribution. Badri et al. (2013) introduced a novel optimization model for multi-echelon, multi-product SCND considering different time resolutions for strategic and tactical decisional levels. The aim of the model is to maximize the total net income over the considered planning period considering the investment of opening and operating facilities as well as the operative costs of raw materials, production, inventory and distribution. To solve the model, the Authors implemented an approach based on Lagrangian Relaxation, following a frequently adopted technique to solve complex facility location problems. Kannegiesser et al. (2015) focused on the long-term design of sustainable supply networks defining a model to minimize the Time-to-Sustainability. This is the time to achieve predefined targets of sustainability and a supply chain reaching a sustainable steady state. Shaw et al. (2016) defined an optimization model addressing carbon-trading issues, setting the optimal material flows and the emissions along the supply chain network to minimize the overall cost. To manage the complexity of the problem, the Authors used Benders decomposition, which is a mathematical programming technique allowing the solution of large problems with a special block solution. Such a structure often occurs in stochastic programming applications governed by uncertainty. Zokaee et al. (2017) proposed an optimization model supporting the sustainable SCND under demand uncertainty considering supply capacity and cost data. The goal is the minimization of the total network cost including the costs of plants and warehouses, shipping costs of raw materials and final products as well as the shortage costs. The Authors used robust optimization, to manage optimization problems in which a certain degree of robustness is adopted to cope with uncertainty. Zheng et al. (2019) studied the integrated optimization of location, stock and routing in a SCND problem, minimizing a total cost function, including the fixed cost of opening the distribution centres, the expected annual inventory cost and the transportation cost, solving it using Benders decomposition.

The literature analysis on single-objective optimization for SCND highlights that the cost minimization is the most widespread and explored parameter when designing supply chain networks. On the other hand, in the field of multi-objective models, a wide number of studies proposed traditional SCND models capturing the trade-off between the total network cost and its environmental impact (Ramudhin et al., 2010; Wang et al., 2011; Memari et al., 2015; Rasi and Sohanian, 2020). Moreover, Chaabane et al. (2012) and Pishvaee and Razmi (2012) faced the SCND problem proposing optimization models simultaneously considering the

minimization of environmental impacts in addition to the traditional economic objectives and using Life Cycle Assessment (LCA) methodology to quantify the environmental impact of different supply chain configurations. Pishvaee et al. (2010) proposed a bi-objective model for the integrated design of forward and reverse logistic networks with the goal to minimize the total network cost and to maximize the system responsiveness. To determine the set of non-dominated solutions, the Authors used a multi-objective memetic algorithm, which is based on a dynamic search strategy by employing three different local searches. Eskandarpour et al. (2013) developed a multi-objective post-sales logistic network design model considering strategic and tactical decision levels, with the aim to minimize total costs, total tardiness and the environmental pollution. To cope with the model complexity, the Authors used a parallel multi-objective heuristic method based on variable neighborhood search to find the set of Pareto optimal solutions. Then, this method was compared with a multi-objective memetic algorithm. Zhang et al. (2016) introduced a new strategic multi-objective model for SCND with multiple distribution channels addressing sustainable objectives, i.e., reducing the cost and the environmental impact and enlarging the customer coverage, solving it by applying an artificial bee colony algorithm. Ghaithan et al. (2017) defined a multi-objective model to support tactical decisions in the Oil & Gas supply chain considering, as objectives, the minimization of the total cost, the maximization of the total revenue and of the service level. The Authors adopted the improved augmented *ε-constraint* method and the CPLEX software to solve the model. Samadi et al. (2018) proposed a three-objective optimization model for a SCND problem optimizing the total cost of the network, the environmental impact and a social function expressed in terms of fixed job opportunities and work's damages. To solve the model, the Authors proposed heuristics as suitable procedures to generate the initial populations, e.g., the red deer algorithm. Peng et al. (2019) introduced a multi-objective formulation for the design of an integrated production-inventory-distribution network. The economic and environmental goals are measured through the total network cost and the greenhouse gas emissions, while a third social objective is proposed and expressed through the impact of accident risk. The augmented *ε-constraint* method was adopted to solve the model. Zarbakhshnia et al. (2019) defined a multi-objective model supporting the design and planning of a green forward and reverse multi-stage multi-product logistic network. The aim was to minimize the total network cost, the environmental emissions and the number of machines in the production line. In terms of solution methodology, an *ε-constraint* method is used to get the set of Pareto solutions. Gruzauskas et al. (2018) integrated Industry 4.0 practices into SCM

addressing, through an industrial case study, the trade-off between sustainability and cost performances by using autonomous vehicles, big data analytics and cyber-physical systems. Mohammed and Duffuaa (2020) faced the optimal design of supply chain networks including in their model the maximization of the profit, the minimization of the risk and of the total supply chain emissions. The aim of this model was to select the best suppliers, to decide plants, distribution and warehouse centers to establish, and to determine the product flows among the network nodes. A tabu search algorithm suitable for multi-product, multi-objective and multi-stage supply chain design problems was proposed. The results of the algorithm are compared against those obtained by an improved augmented *ε-constraint* method.

The literature findings stress that the most of the existing SCND formulations propose single- and bi-objective models addressing traditional economic and/or environmental goals. Three-objective model formulations integrating these traditional objectives to novel issues, e.g., profit, revenues, risk factors, etc., are rising just in the last years, as highlighted in Table 1, which provides a comprehensive review and classification of some relevant literature in the field of SCND against widespread metrics of analysis. However, the integrated design of sustainable supply chain networks considering economic, environmental and lean aspects, in terms of stock minimization, is not yet explored, even if highly expected. In the modern context of Industry 4.0, the mass customization paradigm is responsible of a relevant increase of industrial companies' production mix, resulting in a huge number of variants, which cannot be managed by traditional production strategies, as MTS, because of the high costs that would rise. Hence, even if stock minimization is a key competitive asset to consider, Table 1 highlights the lack of studies considering this relevant aspect in SCND.

In such a dynamic scenario, this paper proposes and applies a novel three-objective optimization model for the SCND minimizing the production, storage and distribution costs associated to the network, i.e., economic objective function, the environmental emissions generated by the production, distribution and storage, i.e., environmental (green) objective function, and the stock level at the network nodes, i.e., lean objective function. The model is presented and described in the next Section 3.

Table 1. Literature contribution classification (SOO = Single-objective optimization, BOO = Bi-objective optimization, TOO = Three-objective optimization).

Id.	Design target				Problem formulation			Solving method		Reference
	Economic	Green	Stock	Other	SOO	BOO	TOO	Solver	Algorithm/Euristics	
1	✓				✓			✓		Pishvaee et al., 2009
2	✓				✓				✓	Nagurney, 2010
3	✓			✓		✓			✓	Pishvaee et al., 2010
4	✓	✓				✓		✓		Ramudhin et al., 2010
5	✓	✓				✓		✓		Wang et al., 2011
6	✓	✓				✓		✓		Chaabane et al., 2012
7	✓	✓				✓		✓		Pishvaee and Razmi, 2012
8	✓				✓				✓	Badri et al., 2013
9	✓	✓		✓			✓		✓	Eskandarpour et al., 2013
10				✓	✓					Kannegiesser et al., 2015
11	✓	✓				✓			✓	Memari et al., 2015
12	✓				✓				✓	Shaw et al., 2016
13	✓	✓		✓			✓		✓	Zhang et al., 2016
14	✓			✓			✓	✓		Ghaithan et al., 2017
15	✓				✓			✓		Zokaee et al., 2017
16	✓	✓		✓			✓		✓	Samadi et al., 2018
17	✓	✓		✓			✓		✓	Zarbakhshnia et al., 2019
18	✓				✓				✓	Zheng et al., 2019
19		✓		✓			✓		✓	Mohammed and Duffuaa, 2020
20	✓	✓		✓			✓	✓		Peng et al., 2020
21	✓	✓				✓			✓	Rasi and Sohanian, 2020
22	✓	✓	✓				✓	✓		*this paper*

3. Problem statement and model formulation

The proposed model addresses the integrated economic, environmental and lean design of a production and distribution supply chain network with three levels, i.e., production plants, distribution centres (DCs) and final customers, which are the network nodes, and two stages. The goal is to minimize the stock level at DC and customer warehouses, i.e., lean function, the environmental emissions for production, shipments from production plants to DCs and from DCs to customers, and storage at the DC and customer warehouses, i.e., green function, and the global production, distribution and storage cost, i.e., economic function. Figure 1 shows a reference schematic of the network structure.
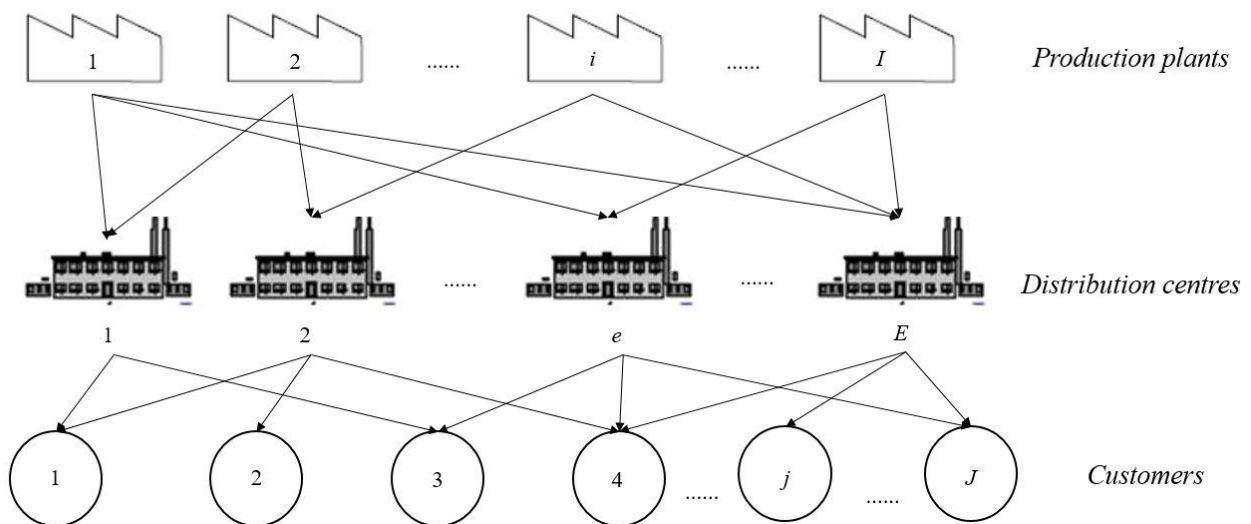
Figure 1. Schematic of the production and distribution supply chain network

Production plants make products and manage their distribution according to the available supply capacity and the market demand of each destination, i.e., customer. Products pass through DCs, which have their own storage capacity and act as temporary storage areas. DCs deliver the products to the customers, having their local warehouses for possible storage at the place of consumption. The proposed model determines the optimal volumes to be shipped from each source to each destination to simultaneously minimize the stock level at DC and customer warehouses, the emissions generated by production, shipments and storage, and the global production, storage and distribution cost.

The proposed mid-term three-objective linear programming model is based on the following assumptions:

✓ the existence of a single product is supposed, i.e., single-product model;

✓ a three-level and two-stage production and distribution supply chain network is considered, i.e., products are made by production plants and, before arriving at final customers, they pass through DCs, which act as temporary storage areas;

✓ the existing travels are between production plants and DCs and between DCs and customers;

✓ according to the mid-term timing horizon, the duration of each planning period guarantees the entire execution of the flows;

✓ storage is at DC and customer warehouses, only;

✓ product quantities are measured in mass (tons), emissions in tonCO2-eq and cost in euros;

✓ economies of scale affect production costs.

The following notations are introduced and used in the following:

o Indices

e Distribution centres, $e = 1, \dots, E$

i Production plants, $i = 1, \dots, I$

j Customers, $j = 1, \dots, J$

k Shipping modes, $k = 1, \dots, K$

o Cost-quantity zones, $o = 1, \dots, O$

t Planning period, $t = 1, \dots, T$

o Parameters

A_{io} Upper limit to the production quantity in zone o for production plant i [ton]

B_e Environmental emission of the distribution centre warehouse e $\left[\frac{\text{tonCO}_{2\text{eq}}}{\text{ton}}\right]$

B_i Environmental emission of the production plant i $\left[\frac{\text{tonCO}_{2\text{eq}}}{\text{ton}}\right]$

B_j Environmental emission of the customer warehouse j $\left[\frac{\text{tonCO}_{2\text{eq}}}{\text{ton}}\right]$

B_k Environmental emission of the shipping mode k $\left[\frac{\text{tonCO}_{2\text{eq}}}{\text{km}}\right]$

c_k Variable shipping cost through shipping mode k $\left[\frac{\text{€}}{\text{km}}\right]$

$cfix_k$ Fixed shipping cost of the shipping mode k $\left[\frac{\text{€}}{\text{trip}}\right]$

D_{jt} Market demand of customer j in period t [ton]

d_{ej} Distance between distribution centre e and customer j [km]

d_{ie} Distance between production plant i and distribution centre e [km]

g_{start_e} Stock at distribution centre warehouse e at the beginning of period $t = 1$ [ton]

g_{start_j} Stock at customer warehouse j at the beginning of period $t = 1$ [ton]

h_e Storage cost at distribution centres $\left[\frac{€}{\text{ton·period}}\right]$

h_j Storage cost at customer warehouses $\left[\frac{€}{\text{ton·period}}\right]$

p_{io} Production cost of production plant i in zone o $\left[\frac{€}{\text{ton}}\right]$

Q_k Nominal capacity of the shipping mode k [ton]

W_e Storage capacity of distribution centre e warehouse [ton]

W_j Storage capacity of customer j warehouse [ton]

○ Decisional variables

b_{iot} 1 if the production quantity of plant i in period t falls in a zone greater or equal to o; 0 otherwise [binary]

g_{et} Stock at the distribution centre warehouse e at the beginning of period t [ton]

g_{jt} Stock at the customer warehouse j at the beginning of period t [ton]

q_{ejkt} Product flow from distribution centre e to customer j in period t with the shipping mode k [ton]

q_{iekt} Product flow from production plant i to distribution centre e in period t with the shipping mode k [ton]

v_{ejkt} Number of trips from the distribution centre e to the customer j in period t with the shipping mode k [#]

v_{iekt} Number of trips from the production plant i to the distribution centre e in period t with the shipping mode k [#]

z_{iot} Produced quantity at the production plant i in period t and zone o [ton]

o Objective functions and bounds

ξ_d Dual objective bound

ξ_p Primal objective bound

ψ^C Production, distribution and storage costs [€]

ψ^G Production, distribution and storage emissions [tonCO$_{2\text{-eq}}$]

ψ^L Stock level at warehouses [ton]

3.1 Mid-term optimization model description

The analytic formulations of the three objective functions are as follows.

$$\min \psi^L = \sum_{j=1}^{J}\sum_{t=1}^{T} g_{jt} + \sum_{j=1}^{J}\left(g_{jT} + \sum_{e=1}^{E}\sum_{k=1}^{K} q_{ejkT} - D_{jT}\right) + \sum_{e=1}^{E}\sum_{t=1}^{T} g_{et} + \sum_{e=1}^{E}\left(g_{eT} + \sum_{i=1}^{I}\sum_{k=1}^{K} q_{iekT} - \sum_{j=1}^{J}\sum_{k=1}^{K} q_{ejkT}\right) \tag{1}$$

$$\min \psi^G = \sum_{i=1}^{I}\sum_{o=1}^{O}\sum_{t=1}^{T} B_i \cdot z_{iot} + \sum_{i=1}^{I}\sum_{e=1}^{E}\sum_{k=1}^{K}\sum_{t=1}^{T}\left(B_k \cdot d_{ie} \cdot v_{iekt}\right) + \sum_{e=1}^{E}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T}\left(B_k \cdot d_{ej} \cdot v_{ejkt}\right)$$

$$+ \sum_{e=1}^{E} B_e \cdot \left(\sum_{t=1}^{T} g_{et} + g_{eT} + \sum_{i=1}^{I}\sum_{k=1}^{K} q_{iekT} - \sum_{j=1}^{J}\sum_{k=1}^{K} q_{ejkT}\right)$$

$$+ \sum_{j=1}^{J} B_j \cdot \left(\sum_{t=1}^{T} g_{jt} + g_{jT} + \sum_{e=1}^{E}\sum_{k=1}^{K} q_{ejkT} - D_{jT}\right) \tag{2}$$

$$\min \psi^C = \sum_{i=1}^{I}\sum_{o=1}^{O}\sum_{t=1}^{T} p_{io} \cdot z_{iot} + \sum_{i=1}^{I}\sum_{e=1}^{E}\sum_{k=1}^{K}\sum_{t=1}^{T}\left(c_k \cdot d_{ie} + cfix_k\right) \cdot v_{iekt}$$

$$+ \sum_{e=1}^{E}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T}\left(c_k \cdot d_{ej} + cfix_k\right) \cdot v_{ejkt}$$

$$+ \sum_{e=1}^{E}\sum_{t=1}^{T} h_e \cdot g_{et} + \sum_{e=1}^{E}\left(g_{eT} + \sum_{i=1}^{I}\sum_{k=1}^{K} q_{iekT} - \sum_{j=1}^{J}\sum_{k=1}^{K} q_{ejkT}\right)$$

$$+ \sum_{j=1}^{J}\sum_{t=1}^{T} h_j \cdot g_{jt} + \sum_{j=1}^{J}\left(g_{jT} + \sum_{e=1}^{E}\sum_{k=1}^{K} q_{ejkT} - D_{jT}\right) \tag{3}$$

Equation (1) models the minimization of the stock level at customer and DC warehouses. For each node, the cumulative stock is the sum of all g_{jt} and g_{et} values plus the stock level at the end of the last period. Equation (2) minimizes the emissions generated by production, i.e., first term of the equation, by product distribution from production plants to DCs and from DCs to customers, i.e., second term of the equation, and by product storage at DCs and customer warehouses, i.e., third and fourth terms of the equation, respectively, over the considered planning periods. Equation (3) minimizes the production costs, considering the existence of economies of scale (Figure 2), i.e., first term of the equation, the product distribution costs among the network nodes at the two stages of the supply chain, i.e., second and third terms of the equation, and the storage costs at DC and customer warehouses, i.e., fourth and fifth terms.
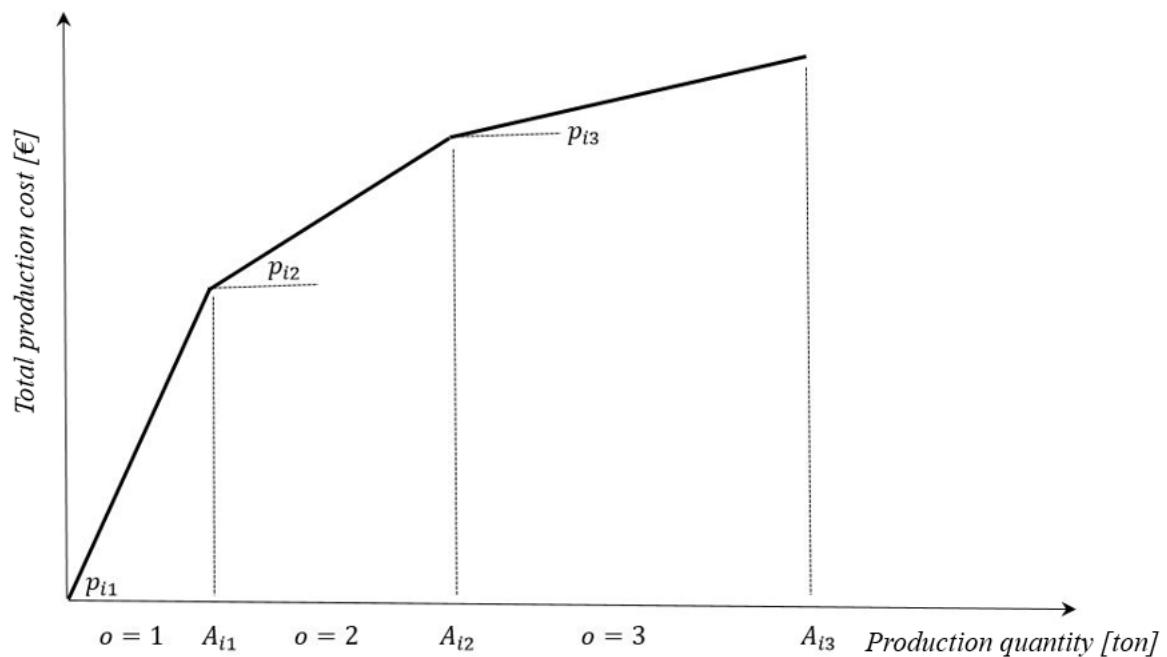
Figure 2. Mathematical framework for economies of scale modelling

In microeconomics, the economies of scale represent the cost benefits that companies get by scaling their operations, and they are traditionally measured by the amount of output produced. In particular, a decrease in the cost per unit of the produced output allows an increase in scale. This concept originates from the economist Adam Smith and from the idea of getting larger production returns through the use of division of labor (O'Sullivan and Sheffrin, 2003). In the proposed model, the presence of economies of scale in the production

cost implies that big batches have unitary cost per ton lower than small batches. To analytically model this logic (Figure 2), a given number of cost-quantity zones (index o) is considered, e.g., three in the figure as a reference example, each of them is linked to an upper value of production quantity (parameter A_{io}). If a production quantity falls in zone o, it is associated to a specific unitary production cost (parameter p_{io}). According to the economies of scale principle, moving from zone o to zone $o + 1$, i.e., by increasing the production quantity, the unitary production cost, i.e., p_{io}, decreases. The upper production quantity value of the last zone (O), i.e., A_{i3} in the reference figure, equals the maximum production capacity of the considered plant. The variable z_{iot} specifies the product quantity produced in production plant i in period t and included in zone o to meet the market demand, while the term $p_{io} \cdot z_{iot}$ computes the production cost of the production plant i in period t considering zone o. Due to the above-described reasons, by plotting such two factors, as in Figure 2, the total production cost, i.e., $p_{io} \cdot z_{iot}$, increases with the increase of the produced and delivered quantity, i.e., z_{iot}, with a less-than-linear trend.

The following feasibility constraints give consistence to the model:

$$g_{jt} + \sum_{e=1}^{E} \sum_{k=1}^{K} q_{ejkt} \geq D_{jt} \qquad\qquad \forall j, t \qquad\qquad (4)$$

$$g_{j1} = g_{start_j} \qquad\qquad \forall j \qquad\qquad (5)$$

$$g_{e1} = g_{start_e} \qquad\qquad \forall e \qquad\qquad (6)$$

$$g_{jt-1} + \sum_{e=1}^{E} \sum_{k=1}^{K} q_{ejkt-1} - D_{jt-1} = g_{jt} \qquad\qquad \forall j, t = 2, \dots, T \qquad\qquad (7)$$

$$g_{et-1} + \sum_{i=1}^{I} \sum_{k=1}^{K} q_{iekt-1} - \sum_{j=1}^{J} \sum_{k=1}^{K} q_{ejkt-1} = g_{et} \qquad\qquad \forall e, t = 2, \dots, T \qquad\qquad (8)$$

$$g_{jt} \leq W_j \qquad\qquad \forall j, t \qquad\qquad (9)$$

$$g_{et} \leq W_e \qquad\qquad \forall e, t \qquad\qquad (10)$$

$$g_{jT} + \sum_{e=1}^{E} \sum_{k=1}^{K} \left(q_{ejkT} - D_{jT} \right) \leq W_j \qquad\qquad \forall j \qquad\qquad (11)$$

$$g_{eT} + \sum_{i=1}^{I}\sum_{k=1}^{K} q_{iekT} - \sum_{j=1}^{J}\sum_{k=1}^{K} q_{ejkT} \leq W_e \qquad \forall\, e \qquad (12)$$

$$\frac{q_{iekt}}{Q_k} \leq v_{iekt} < 1 + \frac{q_{iekt}}{Q_k} \qquad \forall i,e,k,t \qquad (13)$$

$$\frac{q_{ejkt}}{Q_k} \leq v_{ejkt} < 1 + \frac{q_{ejkt}}{Q_k} \qquad \forall e,j,k,t \qquad (14)$$

$$z_{iot} \leq A_{io} \cdot (b_{iot} - b_{io+1t}) \qquad \forall\, i,t \;\; o = 1,\dots O-1 \qquad (15)$$

$$z_{iOt} \leq A_{iO} \cdot b_{iOt} \qquad \forall\, i,t \qquad (16)$$

$$z_{iot} \geq A_{io-1} \cdot (b_{iot} - b_{io+1t}) \qquad \forall\, i,t \;\; o = 2,\dots O-1 \qquad (17)$$

$$z_{iOt} \geq A_{iO-1} \cdot b_{iOt} \qquad \forall\, i,t \qquad (18)$$

$$b_{iot} \geq b_{io+1t} \qquad \forall\, i,t \;\; o = 1,\dots O-1 \qquad (19)$$

$$\sum_{o=1}^{O} z_{iot} = \sum_{e=1}^{E}\sum_{k=1}^{K} q_{iekt} \qquad \forall\, i,t \qquad (20)$$

$$b_{iot} \; binary \qquad \forall\, i,o,t \qquad (21)$$

$$g_{et} \geq 0 \qquad \forall\, e,t \qquad (22)$$

$$g_{jt} \geq 0 \qquad \forall\, j,t \qquad (23)$$

$$q_{ejkt} \geq 0 \qquad \forall\, e,j,k,t \qquad (24)$$

$$q_{iekt} \geq 0 \qquad \forall\, i,e,k,t \qquad (25)$$

$$v_{ejkt} \geq 0, \text{integer} \qquad \forall\, e,j,k,t \qquad (26)$$

$$v_{iekt} \geq 0, \text{integer} \qquad \forall\, i,e,k,t \qquad (27)$$

$$z_{iot} \geq 0 \qquad \forall\, i,o,t \qquad (28)$$

Equation (4) guarantees the demand satisfaction. Equations (5) and (6) define the stock level in period $t = 1$ at the customer and DC warehouses, respectively. Equations (7) and (8) define the stock level at the customer and DC warehouses, respectively, in all the other periods, while, for each period, Equations (9) to (12) limit the stock level to the maximum storage capacity of the customer and DC warehouses. Equations (13) and (14) set the integer number of trips required to move the product from the production plants to the DCs and from the DCs to the customers, respectively, as the ratio between the product flow among two nodes and the capacity of the selected shipping mode. Equations (15) to (19) model the economies of scale of production following the logic described in Figure 2. Analytically, Equations (15) and (16) force the quantity produced in a specific

period, plant and zone not to exceed the upper value for that zone. On the other hand, Equations (17) and (18) force the quantity produced in a specific period, plant and zone to be higher than the upper value of the maximum production quantity associated to the previous zone. Equation (19) sets the variable b_{iot}; if the production quantity falls is a given cost-quantity zone o, for all zones from 1 to o, the parameter b_{iot} is set to 1, while for the remaining zones, from $o + 1$ to O, b_{iot} is set to 0. Equation (20) links the quantity produced in the production plant i in the period t to the product flows starting from i in that period. Finally, Equations (21) to (28) give consistence to all the decisional variables. The model has $2 \cdot E \cdot K \cdot T \cdot (J + I) + T \cdot (2 \cdot I \cdot O + E + J)$ variables and $I \cdot T \cdot (3 \cdot O - 1) + E \cdot K \cdot T \cdot (I + J) + T \cdot (3 \cdot J + 2 \cdot E)$ constraints, plus the variable consistency constraints.

The next Section 4 applies the proposed model to a European supply chain network and discusses the main results and key findings.

4. Industrial application

The proposed model is applied to an industrial case study, representative of a European production and distribution supply chain network, shipping bulk material to companies operating in the civil building sector. The network structure includes five production plants, ten DCs and fifty customers aggregated by their geographical locations. Three different road vehicles are available for the product shipments, i.e., VAN, truck and lorry. The planning horizon includes twelve months with a monthly resolution, while six different cost-quantity zones are available for each production plant to set economies of scale in production costs. Despite the green objective function, i.e., Equation 2, includes the environmental emissions caused by production, distribution and storage activities, in the solving phase the emissions caused by the product distribution are considered, only, because of their expected high incidence and to stress the need of balance between lean management and environmental sustainability, i.e., in outbound logistics, the replenishment frequency is a major point of collision between these two perspectives (Carvalho et al., 2011). According to the JIT principles, the lean perspective benefits from high shipment frequencies of small product batches, to minimize the warehouse stock level (Ugarte et al., 2016). On the other side, the environmental sustainability perspective benefits from low full-load shipments to minimize the CO_2 emissions generated by shipping. Such opposite

trend increases for large-scale networks, as in the case of the present industrial application. A schematic of the network geography is in Figure 3.

Figure 3. Supply chain network geography, production plants (in red), DCs (in green) and customers (in blue)

The input parameters to feed the model are collected from the field, e.g., customer forecast database, company Material Requirement Planning (MRP), transportation fleet, etc., while the environmental data are collected using dedicated databases accessed through *SimaPro 7.3.3 by PRé Consultants* software (Amersfoort, The Netherlands). Detailed data are collected in Appendix A, while Figure 4 shows, per each production plant, the relation between the production quantity and the unitary production cost, i.e., p_{io}. This cost decreases moving from one zone to the next one, as effect of the economies of scale. Figure 4 follows the logic detailed in the previous Figure 2, focusing on unitary production cost instead of the total cost.
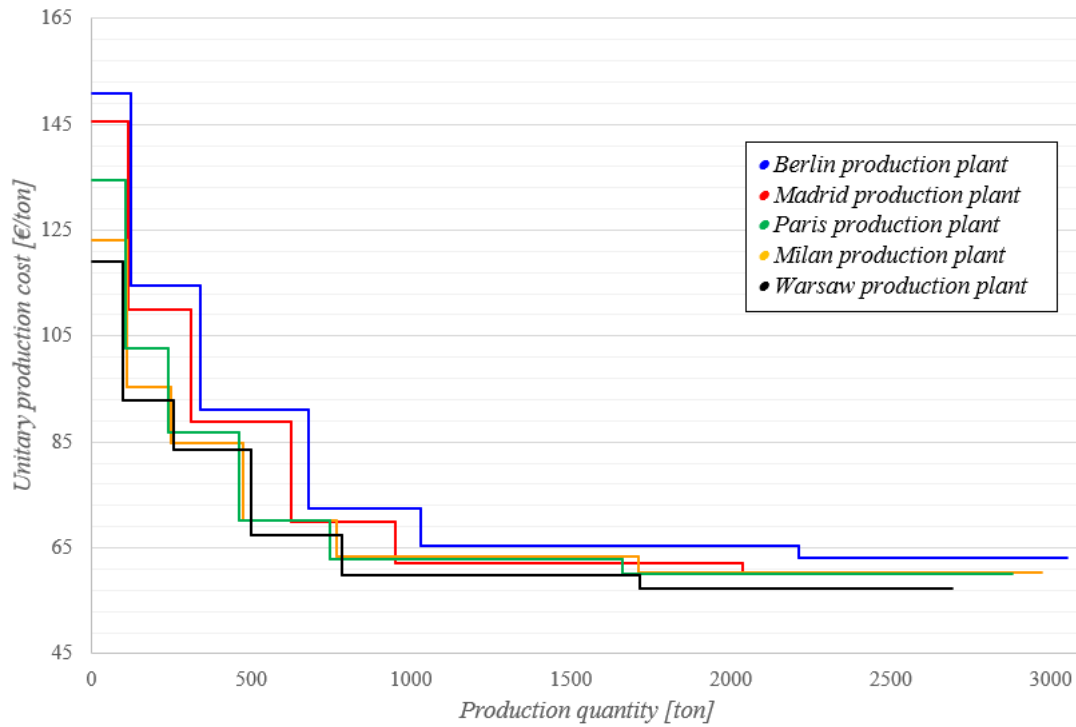
Figure 4. Unitary production cost function for the five production plants

As example, if 100 tons are supplied by the Madrid production plant, a production cost of about 145.50 €/ton is applied; otherwise, if 120 tons are supplied, the production cost lowers to 110 €/ton, etc. Detailed data about the production capacity and the production costs of the plants together with the upper limits used to set the economies of scale are in Table A1 of Appendix A. The storage capacity is set to 4'000 tons for all DC and customer warehouses and their initial stock is null, while the storage cost is set to 15.84 €/ton for all DCs, i.e., h_e, and to 25.34 €/ton for all customers, i.e., h_j. Finally, the selection of the most suitable shipping mode, for production plant-DC and DC-customer flows, is among the following alternatives:

1. van with a total mass (full load) of 2.7 tons and a payload of 1.2 tons;

2. truck with a total mass (full load) of 15 tons and a payload of 9 tons;

3. lorry with a total mass (full load) of 40 tons and a payload of 25 tons.

The model is coded in AMPL language and processed adopting Gurobi Optimizer© v.5.5 solver through an Intel® Core™ i7-3770 CPU @ 3.40 GHz and 16.0 GB RAM workstation. The solver uses the Simplex algorithm to solve the model. A relevant parameter to set when implementing the Simplex algorithm through Gurobi is the so-called *mipgap* value, i.e., the gap between the lower and the upper objective bound. In detail, if ξ_p is the primal objective bound, i.e., the incumbent objective value, which is the upper bound for the

minimization problems, and ξ_d is the dual objective bound, i.e., the lower bound for the minimization

problems, than:

$$mipgap = \frac{\text{abs }(\xi_p - \xi_d)}{\xi_p} \tag{29}$$

In the solving procedure, the *mipgap* is set to 1%. In addition, among the set of existing methodologies in the

field of multi-objective optimization, the Normalized Normal Constraint Method (NNCM) (Messac et al.,

2003) is used to build the Pareto frontier. This curve is the *locus of points*, within the solution space, that are

not dominated by any other point. For any point of the frontier, improving an objective function without

worsening the performance of the another is not possible. The coordinates of each point of the Pareto frontier

include the values of the stock, i.e., Equation (1), the environmental, i.e., Equation (2), and the economic, i.e.,

Equation (3), objective functions. The solving time is of about two hours per Pareto point. This time fits with

the adoption of the mid-term tactical perspective asking for a low frequency of the model run by industrial

companies. Furthermore, in the case of large industrial instances, among the strategies that can be adopted to

apply the proposed three-objective model, the decomposition of the problem, e.g., by setting geographic

clusters to reduce the model complexity, and the use of heuristic algorithms in the solving phase are promising

paths to explore. The key results are presented and discussed in the following paragraphs of this Section.

4.1 Pareto frontier

Figure 5 presents a 3D view of the solution space obtained by applying the NNCM. The blue points are the

dominated points, while the other 22 points, in red and green, are non-dominated. Focusing on the non-

dominated points, AP_1, AP_2 and AP_3, in green, are the so-called anchor points (APs), computed by solving the

model minimizing the three objective functions separately. Each non-dominated point lies on the Pareto

frontier and it corresponds to a supply chain network configuration.
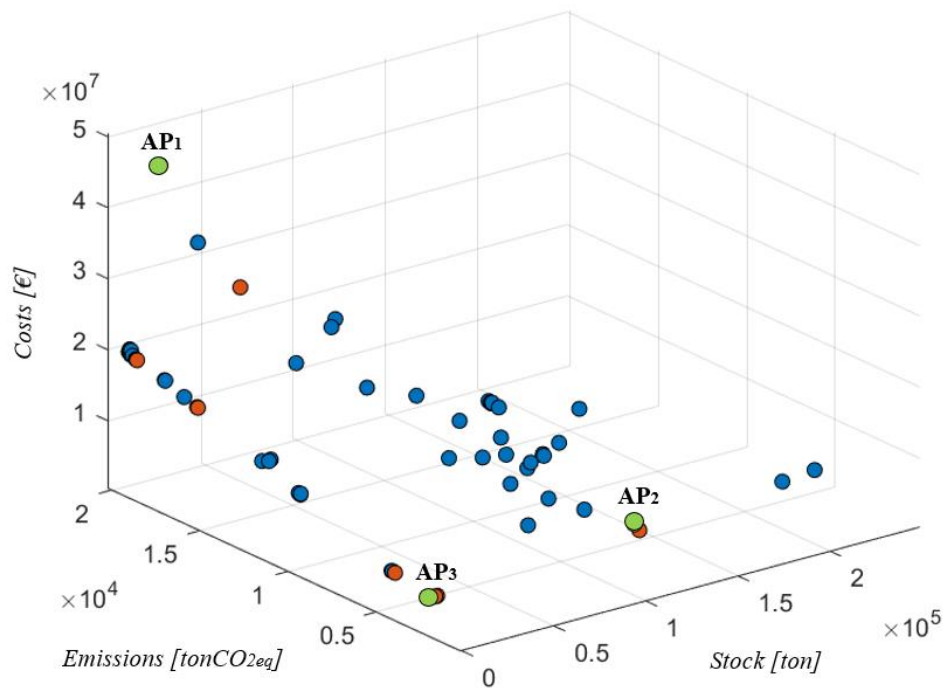
Figure 5. Industrial application, solution space

By minimizing the stock level, i.e., lean function, both DC and customer warehouses have no stock at all time. On the other hand, this solution leads to environmental emissions of 17'286.69 tonCO$_{2\text{-eq}}$ and to a cost function value of 49'194'651.69 € over the whole planning horizon. By minimizing the green function, emissions are of about 2'205.96 tonCO$_{2\text{-eq}}$, while the global cost is equal to 7'962'352.92 € (equal to 187.59 €/ton, on average) and the cumulate stock at the warehouses is of 113'019.32 tons. Such a high value of the stock level is due to full load shipping to reduce CO$_{2\text{-eq}}$ emissions. Finally, by minimizing the economic function, the global production, storage and distribution cost is of about 5'355'060.11 € (average cost per ton of about 126.16 €/ton), while the environmental emissions are of about 2'243.21 tonCO$_{2\text{-eq}}$ and the cumulate stock is of about 5'893 tons. The value of the green indicator, similar to the green AP, is due to the use of fully loaded vehicles to reduce the number of trips and, consequently, the environmental emissions. Table 2 and Table 3 summarize the global and unitary anchor point values, respectively.

Table 2. Anchor point total values.

	Stock [ton]	Green [tonCO2-eq]	Cost [€]
AP1 (stock)	0	17'286.69	49'194'651.69
AP2 (green)	113'019.3	2'205.96	7'962'352.92
AP3 (cost)	5'893	2'243.21	5'355'060.11

Table 3. Anchor point unitary average values.

	Stock [ton/(period · plant)]	Green [tonCO2-eq/ton]	Cost [€/ton]
AP1 (stock)	0	0.41	1'159.02
AP2 (green)	1'883.66	0.052	187.59
AP3 (cost)	98.22	0.053	126.16

The divergent trend of the three objective functions demonstrates the relevance of the proposed industrial application toward the three-objective optimization model. Table 4 reports the coordinates of the non-dominated Pareto points, representing the base to select the final supply chain network configuration, adopting a subjective informal approach.

Table 4. Coordinates of the non-dominated Pareto points.

Pareto point	Stock [ton]	Green [tonCO$_{2\text{-eq}}$]	Cost [€]
AP$_1 \cong$ P$_1$	0.00	17'286.69	49'194'651.69
P$_2$	0.00	18'604.69	20'233'546.22
P$_3$	0.04	15'152.57	17'479'503.23
P$_4$	0.95	12'755.05	37'195'401.88
P$_5$	2.00	3'981.17	7'044'242.31
P$_6$	5'199.00	2'253.09	5'370'333.18
P$_7$	5'206.00	2'241.70	5'366'327.99
P$_8$	5'302.00	2'240.42	5'367'854.46
P$_9$	5'423.00	2'238.82	5'360'620.18
P$_{10}$	5'629.00	2'235.35	5'367'055.37
P$_{11}$	5'656.00	2'237.78	5'359'630.32
AP$_3 \cong$ P$_{12}$	5'893.00	2'243.21	5'355'060.11
P$_{13}$	6'009.00	2'214.32	5'431'416.78
AP$_2 \cong$ P$_{14}$	113'019.32	2'205.96	7'962'352.92
P$_{15}$	115'839.91	2'212.06	6'934'689.99
P$_{16}$	115'841.34	2'212.52	6'934'167.61
P$_{17}$	115'842.37	2'213.17	6'933'785.36
P$_{18}$	115'843.51	2'213.17	6'933'387.30
P$_{19}$	115'845.30	2'212.92	6'932'714.17
P$_{20}$	115'846.40	2'213.06	6'932'519.33
P$_{21}$	115'849.42	2'212.72	6'931'229.22
P$_{22}$	115'851.25	2'213.12	6'930'566.39

4.2 Sensitivity analysis and final network configuration selection

To support the decision makers and the industrial practitioners in the selection of the final network configuration, a heuristic procedure is used. The idea is to ranks the non-dominated Pareto points in Table 4 according to an aggregated score, γ_a, as in Equations (30) to (33).

$$\gamma_a^L = 10 \cdot \frac{\max_b\{P_b^L\} - P_a^L}{\max_b\{P_b^L\} - \min_b\{P_b^L\}} \tag{30}$$

$$\gamma_a^G = 10 \cdot \frac{\max_b\{P_b^G\} - P_a^G}{\max_b\{P_b^G\} - \min_b\{P_b^G\}} \tag{31}$$

$$\gamma_a^C = 10 \cdot \frac{\max_b\{P_b^C\} - P_a^C}{\max_b\{P_b^C\} - \min_b\{P_b^C\}} \tag{32}$$

$$\gamma_a = \frac{\sum_{F \in \{L,G,C\}} \delta^F \cdot \gamma_a^F}{\sum_{F \in \{L,G,C\}} \delta^F} \tag{33}$$

where $a, b = 1, \dots, 22$ are the indices for the non-dominated points, $P_a(P_a^L, P_a^G, P_a^C)$ expresses the coordinates of the non-dominated points in terms of stock, green and cost value, respectively, and δ^F are the weights the decision makers assign to the three objectives, i.e., stock, green and cost.

The scores are in the range [0,10] and they are computed weighting three normalized partial scores, further computed per each Pareto point and target, i.e., stock, γ_a^L, green, γ_a^G, and cost, γ_a^C. The higher the score, the higher the ability to meet lean, green and economic goals simultaneously. Figure 6 plots the Pareto point final scores, considering four main scenarios according to possible choices of the decision makers:

✓ *equal weight scenario* ($\delta^L = \delta^G = \delta^C = 1/3$);

✓ *cost-oriented scenario*, i.e., weight of the economic target doubled compared to the lean and green targets ($\delta^C = 2 \cdot \delta^L = 2 \cdot \delta^G = 1/2$);

✓ *green-oriented scenario*, i.e., weight of the green target doubled compared to the lean and cost targets ($\delta^G = 2 \cdot \delta^L = 2 \cdot \delta^C = 1/2$);

✓ *lean-oriented scenario*, i.e., weight of the lean target doubled compared to the green and cost targets ($\delta^L = 2 \cdot \delta^G = 2 \cdot \delta^C = 1/2$).
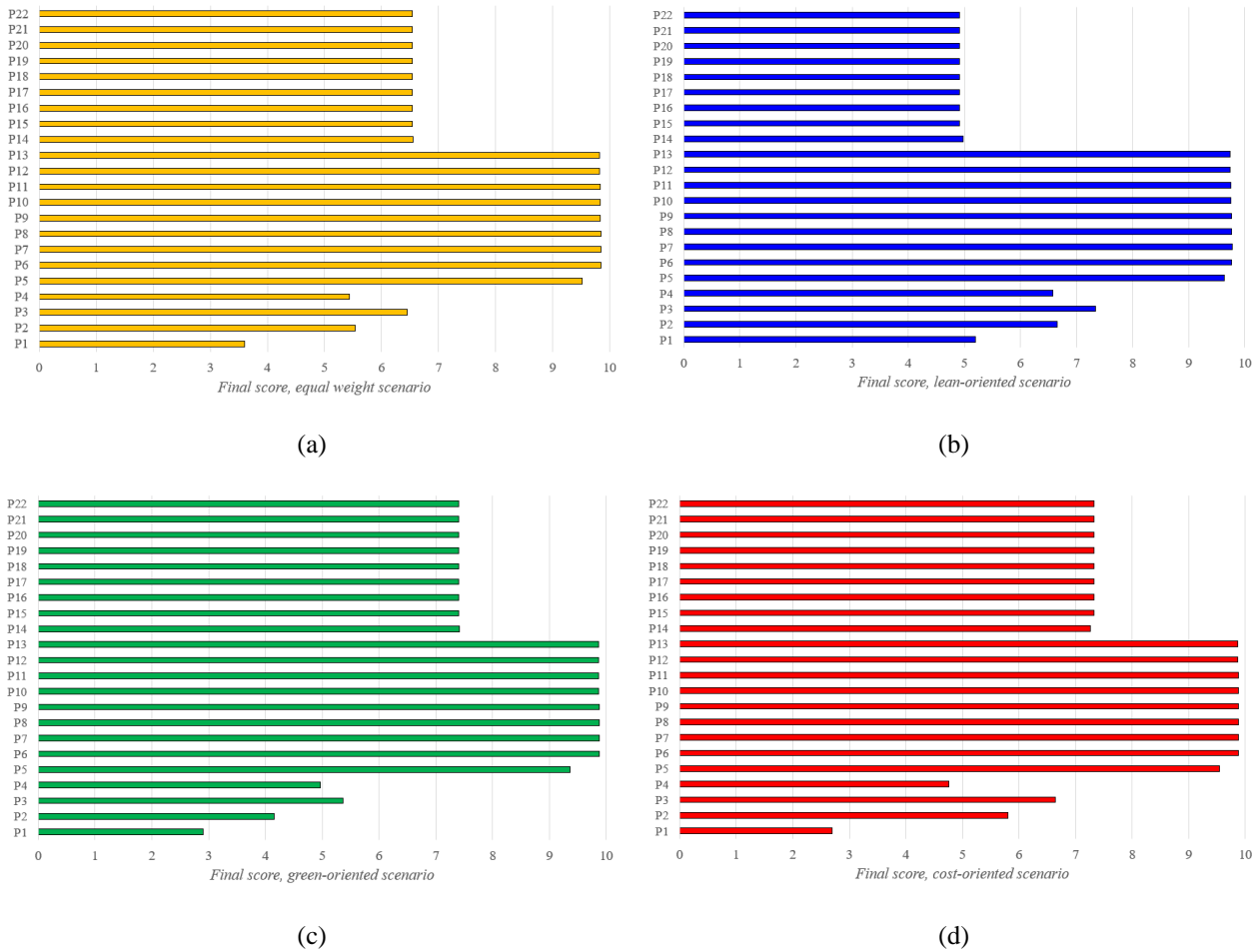
Figure 6. Pareto point final scores for the four scenarios, (a) - (d)

Points from P_6 to P_{13} have a final score higher than 9.7 in all the analysed scenarios. These points show a good balance among the three objective functions, presenting acceptable values of stock levels, emissions and global cost. The Pareto point with the higher global score is P_7 in all scenarios, presenting a stock level of 5'206 tons, emissions equal to 2'241.70 tonCO$_{2\text{-eq}}$ and a global production, storage and distribution cost of about 5'366'327.99 €. Such a solution leads to an average cost per ton of product of about 126.43 €/ton, 0.21% higher than the optimum cost value, which is of about 126.16 €/ton. The emission level is 1.62% higher than the optimum green value and the stock level is 95.50% lower than the lean worst value. This comparison is reported in Figure 7, which shows the stock (Figure 7(a)), green (Figure 7(b)) and economic (Figure 7(c)) performances of the chosen point P_7 and of the three APs. In addition, for P_7, Figure 8 details the stock, environmental and cost drivers of the chosen supply chain network configuration.
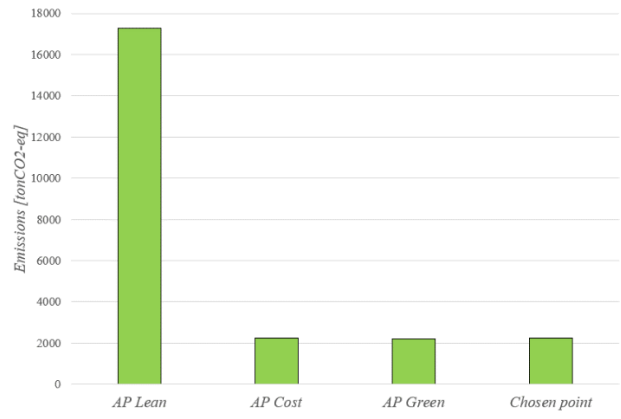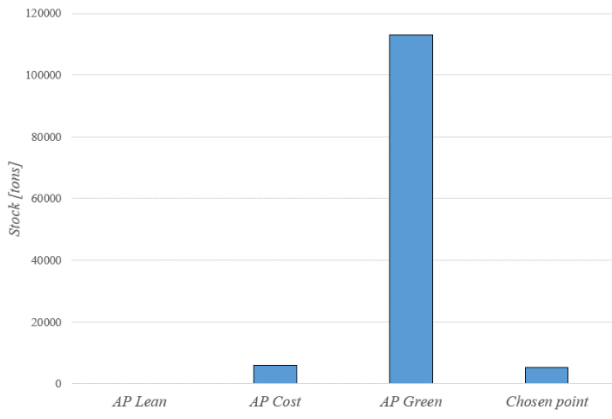
(a)

(b)
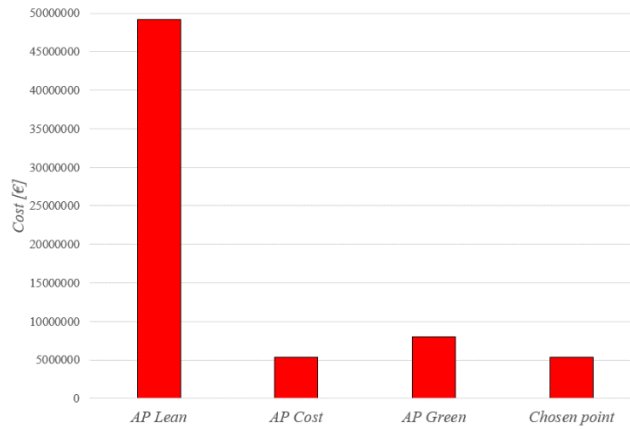
(c)

Figure 7. Stock (a), environmental (b) and cost (c) comparative analysis

(a)

(b)

Costs

- Production (51%)
- Plant-DC transport (15%)
- DC-customer transport (32%)
- Storage (2%)

(c)
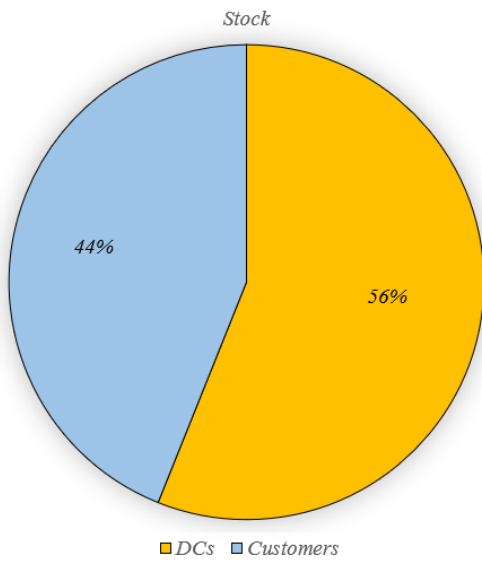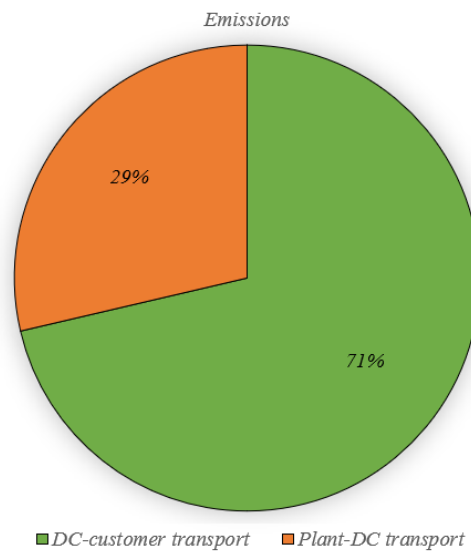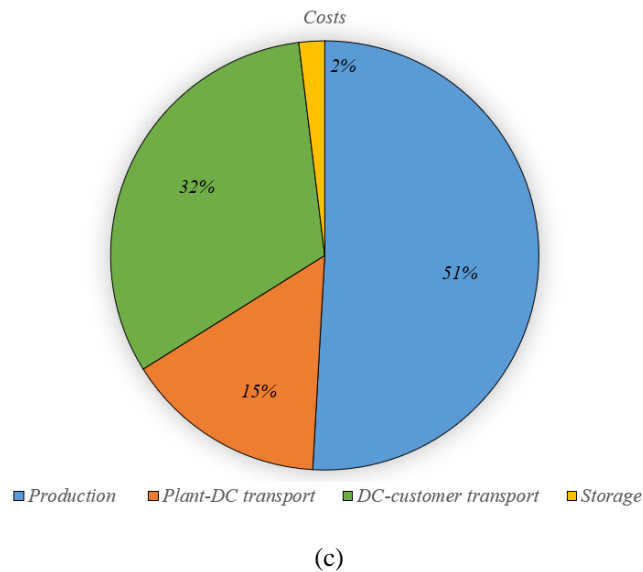
Figure 8. Stock (a), environmental (b) and cost (c) drivers for Pareto point P_7

Production covers the 51% of the total costs, transport covers the 47%, including both production plant-DC and DC-customer flows, and, finally, the remaining 2% is associated to storage. Concerning the environmental impact, the most significant contribution is the transport from the DCs to the final customers, i.e., 71% of the total emissions. Finally, by analyzing the inventory levels, they are almost equally distributed between DC and customer warehouses. The slight preference of stocking at the DCs is due to their lower inventory cost compared to the customer warehouses.

Finally, Figure 9 shows a geographic representation of the logistic flows among the network nodes for the selected supply chain network configuration, i.e., P_7, and in the three APs, i.e., economic, green and stock single-objective optima. The arrow thickness is proportional to the number of trips between each couple of nodes. Moreover, the red lines represent trips between production plants and the DCs, while the black lines connect DCs to the final customers.

(a)
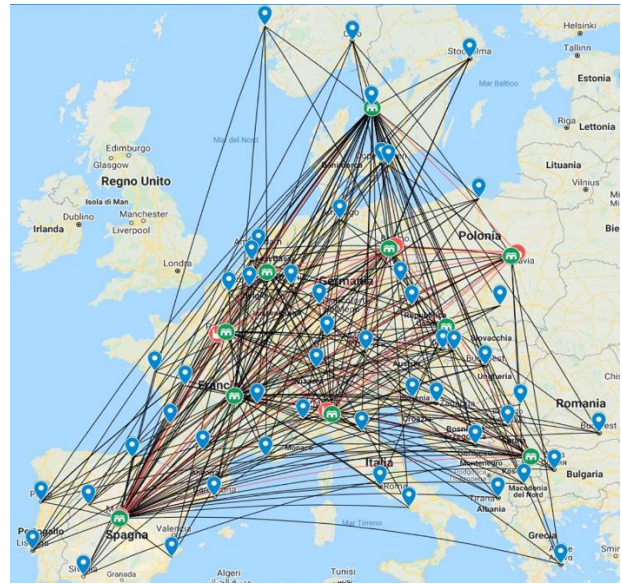
(b)

(c)

(d)

Figure 9. Supply chain network flows for the selected optimum P_7 (a) and stock (b), environmental (c) and

cost (d) APs

In each configuration, i.e., in the three APs and in the selected point P_7, flows between couples of nodes are

assessed by building *plant x DC* and *DC x customer* matrices containing the number of flows between the

couple of nodes. These matrices are in the supplementary material of this paper, while the main results are in

Table 5 and Table 6 which show the average number of trips among couples of network nodes, per period, for

each configuration, together with the average travelled distance, in km. Such tables provide, also, information

about the percentage of the matrix *empty* cells in the analysed configurations. Such cells state the absence of flow between the source and the destination nodes.

Table 5. Average number of trips and travelled distance between plants and DCs.

Configuration	Average trips [trips/period]	Average distance [km/period]	% empty cells
Chosen point (P7)	11.85	28'485.08	76
AP1 (lean)	40.85	1'589'115.25	18
AP2 (green)	17.73	26'457.75	84
AP3 (cost)	11.89	28'912.33	76

Table 6. Average number of trips and travelled distance between DCs and customers.

Configuration	Average trips [trips/period]	Average distance [km/period]	% empty cells
Chosen point (P7)	1.98	71'292.17	85
AP1 (lean)	4.84	2'100'068.25	46
AP2 (green)	2.77	71'882.58	90
AP3 (cost)	1.85	71'272.83	84

Globally, the supply chain network configuration corresponding to P_7 leads to low average trips and travelled distance among the network nodes, similarly to the economic and green APs. Moreover, such configurations prefer the use of large capacity shipping modes to decrease the number of trips and, as a consequence, the shipping cost and the environmental emissions. On the other hand, the network configuration for the lean AP is characterized by significant values of the average trips and travelled distance among the network nodes as well as by a low percentage of empty cells because of the need to continuously supply products to DCs and customers to minimize the global stock. Furthermore, the lean supply chain configuration prefers the use of low-capacity shipping modes to deliver the products to DCs and customers, frequently. This choice generates a significant number of trips among the network nodes. Globally, within the proposed industrial application, P_7 rises up as a suitable strategic point to balance the economic, green and lean, i.e., stock, goals.

5. Conclusions and future research

Sustainability is a hot topic in the recent literature and it is finding full attention and large application in wide and cross-sectorial disciplines. Supply chain management (SCM) is among the fields in which sustainability is paving the way for its full implementation, from both the economic and environmental perspectives. Furthermore, modern companies live in a dynamic and unstable industrial and market setting governed by Industry 4.0 and the mass customization paradigm. In this context, products cannot be managed with traditional production strategies, as Make-to-Stock (MTS), because of the high cost that would result. To best manage this upcoming trend, stock minimization, which is one of the main goals of the lean production paradigm, rises as a crucial asset to include when designing sustainable supply chain networks. Starting from this background, this paper faces the mid-term sustainable supply chain network design (SCND) proposing and applying a three-objective linear programming optimization model to minimize stock levels, i.e., lean goal, environmental emissions, i.e., green goal, and the overall production, storage and distribution cost, getting the Pareto frontier of the efficient network configurations. An industrial application, representative of a European logistic company, showcases the model adoption. Results highlight that the single-objective focus on stock, environmental and cost impact leads to divergent network configurations stressing the need to best balance opposite trends. For the proposed industrial application, the chosen supply chain network configuration allows reducing stock levels with an increase of the environmental emissions of about 1.62% toward the green optimum, and of the global network cost of about 0.21% toward the optimum value. Future research has to consider multi-product supply chain networks, multi-modal transport, assessing the combined use of different shipping modes, as truck & rail multi-modal configurations, as well as an increase in the length of the channel. In addition, the screening and use of heuristic algorithms needs to be explored in the solving phase to apply the model to large-scale supply chain networks.

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Appendix A

Table A1. Production capacity and production costs data.

Production plant (i)		Zone (o)	Supply capacity (A_{io}) [ton]	Production cost (P_{io}) [€/ton]
Madrid	1	1	115	145.50
Madrid	1	2	310	110.00
Madrid	1	3	625	88.80
Madrid	1	4	950	69.90
Madrid	1	5	2'035	62.20
Madrid	1	6	2'810	60.00
Milan	2	1	110	123.20
Milan	2	2	250	95.50
Milan	2	3	475	84.70
Milan	2	4	765	70.20
Milan	2	5	1'710	63.30

Milan	2	6	2'970	60.40
Paris	3	1	105	134.40
Paris	3	2	240	102.80
Paris	3	3	460	86.80
Paris	3	4	745	70.10
Paris	3	5	1'660	62.80
Paris	3	6	2'880	60.20
Berlin	4	1	125	150.80
Berlin	4	2	340	114.50
Berlin	4	3	680	91.20
Berlin	4	4	1'030	72.40
Berlin	4	5	2'210	65.30
Berlin	4	6	3'050	63.00
Warsaw	5	1	100	119.00
Warsaw	5	2	255	92.80
Warsaw	5	3	500	83.50
Warsaw	5	4	785	67.40
Warsaw	5	5	1715	59.80
Warsaw	5	6	2'690	57.20

Table A2. Industrial case study, customer demand [tons].

Customer	Period											
	1	2	3	4	5	6	7	8	9	10	11	12
Alicante	62	130	86	48	116	130	88	70	88	126	56	68
Amsterdam	138	136	140	88	88	80	84	88	92	130	134	134
Athens	88	112	84	90	86	102	100	90	102	86	92	96
Barcelona	50	52	64	120	124	124	156	128	130	76	68	66
Belgrade	102	102	78	48	52	52	53	54	62	86	96	100
Bergen	54	70	58	82	90	40	76	48	62	60	38	36
Bilbao	10	21	0	0	0	11	0	15	0	0	13	18
Bologna	52	74	78	84	86	90	70	98	104	108	114	120
Bordeaux	0	2	0	0	5	3	0	0	9	1	8	0
Bratislava	102	78	90	132	108	112	76	74	78	64	126	120
Brussels	98	100	100	150	154	156	154	160	164	88	88	96
Bucharest	48	64	74	70	54	58	82	94	82	66	80	90
Budapest	30	30	32	88	92	96	100	100	96	40	36	34
Cologne	68	76	80	24	22	26	91	70	84	30	30	34
Copenhagen	132	124	108	60	58	60	136	120	126	64	68	68
Dresden	70	80	74	140	142	146	102	138	136	84	80	70
Frankfurt am Main	150	148	152	100	100	98	102	100	104	142	146	146

Gdansk	138	130	114	66	60	66	68	74	74	120	126	132
Göteborg	0	0	0	0	4	5	6	0	7	0	8	0
Hamburg	122	112	140	74	122	124	116	128	118	140	110	84
Krakow	1	0	3	4	3	0	2	0	0	3	0	3
Lille	126	108	116	114	90	104	86	76	80	78	102	110
Lisbon	34	34	38	40	42	44	45	46	50	52	54	54
Ljubljana	0	0	8	6	0	1	3	2	0	0	4	4
Lyon	132	130	134	82	82	74	124	128	128	84	82	86
Malmö	82	90	94	38	36	40	42	44	48	76	84	98
Marseille	52	98	106	104	90	78	90	74	82	70	100	96
Munich	108	124	94	102	126	112	103	108	100	110	98	126
Nantes	30	40	42	90	94	98	128	96	96	50	46	48
Naples	84	92	104	70	66	82	85	98	102	86	112	116
Oslo	40	42	54	110	114	114	116	118	120	66	58	56
Poitiers	66	74	78	22	20	24	26	28	32	60	68	82
Porto	20	30	32	80	84	88	92	86	86	40	36	38
Prague	84	88	92	98	100	104	108	112	118	122	128	134
Rome	94	94	70	40	44	44	45	46	54	78	88	92
Rotterdam	76	82	86	88	96	96	98	108	112	114	126	132
Salamanca	116	108	92	44	42	44	124	104	110	48	52	52
Sarajevo	52	54	54	58	60	62	64	66	70	74	78	82
Seville	122	114	98	50	48	50	55	58	58	104	110	116
Skopje	40	40	42	98	102	106	146	110	106	50	46	44
Sofia	120	118	116	40	38	38	113	114	118	42	46	48
Stockholm	76	76	84	88	90	92	96	104	108	110	116	122
Stuttgart	20	20	24	26	28	30	30	36	38	40	40	46
Timisoara	0	0	0	10	12	0	0	8	11	7	0	0
Tirana	2	3	1	0	0	0	0	5	4	4	0	0
Toulouse	38	40	40	44	46	48	52	56	60	64	68	75
Turin	88	88	64	34	38	38	70	82	86	42	40	48
Vienna	144	142	146	94	94	86	152	146	140	96	94	98
Zagreb	96	96	72	42	46	46	110	90	94	50	48	56
Zurich	0	15	0	1	0	1	8	10	0	12	0	5

Table A3. Industrial case study, distances among the production plants and the DCs [km].

DC	Production plant				
	Berlin	Madrid	Milan	Paris	Warsaw
Brno	553	2'417	999	1'238	554
Eindhoven	644	1'700	953	434	1'181
Getafe	1'265	14	1'590	1'284	2'866

Grodzisk Mazowiecki	547	2'830	1'496	1'564	40	
Lodi	1'076	1'607	41	888	1'564	
Meaux	1'035	1'321	867	55	1'590	
Mölndal	729	2'789	1'731	1'523	1'298	
Niš	1'491	2'824	1'258	2'080	1'308	
Potsdam	35	2'300	1'015	1'034	583	
Vichy	1'265	1'108	608	400	1'749	

Table A4. Industrial case study, distances among the DCs and the customers [km].

Customers	DCs									
	Brno	Eindhoven	Getafe	Grodzisk Mazowiecki	Lodi	Meaux	Mölndal	Niš	Potsdam	Vichy
Alicante	2'447	1'961	418	2'853	1'531	1'608	2'932	2'753	2'366	1'213
Amsterdam	1'082	124	1'782	1'165	1'116	492	1'086	2'001	625	885
Athens	1'790	2'761	3'688	2'231	2'098	2'906	3'066	864	2'357	2'714
Barcelon	1'921	1'437	634	2'327	1'018	1'084	2'406	2'227	1'841	687
Belgrade	698	1'672	2'603	1'139	1'006	1'814	1'975	238	1'266	1'622
Bergen	1'944	1'612	3'280	1'982	2'675	2'400	762	2'876	1'799	2'318
Bilbao	2'068	1'346	411	2'475	1'340	964	2'443	2'561	1'935	752
Bologna	864	1'169	1'742	1'398	188	1'078	1'839	1'143	1'113	796
Bordeaux	1'738	1'010	699	2'140	1'037	629	2'107	2'249	1'600	423
Brussels	1'107	130	1'589	1'272	920	299	1'222	1'962	732	691
Bratislava	130	1'136	2'474	648	916	1'270	1'406	806	685	1'354
Bucharest	1'154	2'128	3'355	1'252	1'766	2'263	2'430	474	1'722	2'343
Budapest	328	1'302	2'570	769	944	1'436	1'604	613	896	1'517
Cologne	895	147	1'775	1'084	866	485	1'054	1'751	544	746
Copenhagen	988	807	2'508	975	1'620	1'347	308	1'912	744	1'535
Dresden	352	666	2'315	594	951	980	923	1'276	202	1'135
Frankfurt am Main	714	345	1'865	1'045	703	526	1'115	1'569	516	727
Gdansk	765	1'181	2'864	389	1'611	1'602	850	1'618	582	1'795
Göteborg	1'291	1'111	2'804	1'278	1'923	1'648	10	2'216	1'047	1'840
Hamburg	841	482	2'183	830	1'150	888	630	1'768	284	1'210
Krakow	333	1'180	2'833	282	1'315	1'494	1'381	1'010	622	1'649
Lille	1'214	212	1'499	1'357	1'050	209	1'304	2'069	817	601
Lisbon	2'884	2'162	620	3'291	2'156	1'781	3'259	3'390	2'751	1'568
Ljubljana	514	1'133	2'071	1'032	482	1'203	1'689	768	946	1'096
Lyon	1'285	799	1'249	1'691	485	482	1'769	1'697	1'204	165
Malmö	1'018	837	2'538	1'005	1'650	1'375	264	1'942	774	1'565

Marseille	1'497	1'108	1'115	2'000	539	791	2'079	1'761	1'515	472
Munich	542	725	1'978	1'049	534	795	1'281	1'173	555	857
Nantes	1'610	811	1'046	1'940	1'089	430	1'908	2'296	1'400	524
Naples	1'451	1'727	2'165	1'970	745	1'636	2'397	1'715	1'671	1'354
Oslo	1'619	1'283	2'984	1'600	2'214	1'946	298	2'581	1'338	2'022
Poitiers	1'584	766	951	1'895	910	385	1'863	2'132	1'355	305
Porto	2'733	2'011	577	3'140	2'005	1'629	3'107	3'226	2'600	1'417
Prague	206	807	2'223	611	907	990	1'079	1'130	358	1'110
Rome	1'252	1'530	1'966	1'770	546	1'437	2'197	1'516	1'472	1'154
Rotterdam	1'112	113	1'721	1'202	1'056	431	1'122	2'015	662	824
Salamanca	2'418	1'696	230	2'825	1'690	1'315	2'793	2'918	2'285	1'102
Sarajevo	859	1'638	2'606	1'300	1'015	1'745	2'175	446	1'449	1'631
Seville	2'905	2'161	529	3'290	1'989	1'779	3'257	3'210	2'750	1'567
Skopje	1'127	2'100	3'025	1'568	1'434	2'201	2'403	201	1'694	2'050
Sofia	1'087	2'059	2'985	1'528	1'395	2'124	2'363	159	1'654	2'010
Stockholm	1'632	1'452	3'287	1'619	2'265	1'989	471	2'557	1'388	2'180
Stuttgart	687	507	1'773	1'093	545	570	1'277	1'408	602	660
Timisoara	635	1'609	2'836	1'076	1'247	1'744	1'911	347	1'202	1'824
Tirana	1'392	2'071	2'935	1'865	1'346	2'120	2'629	500	1'903	1'962
Toulouse	1'739	1'104	764	2'145	902	723	2'201	2'123	1'658	423
Turin	1'124	1'099	1'486	1'616	191	793	1'851	1'388	1'125	473
Vienna	140	1'053	2'382	658	850	1'190	1'369	848	648	1'268
Zagreb	493	1'239	2'207	1'024	616	1'346	1'776	627	1'050	1'233
Zurich	880	700	1'660	1'304	320	593	1'516	1'482	813	528

Table A5. Industrial case study, shipping modes.

Shipping mode	Capacity [ton]	Emissions [kgCO2eq/km]	Fix cost [€/trip]	Variable cost [€/km]
Van	1.2	0.302	50	0.931
Truck	9	0.717	100	1.434
Lorry	25	1.879	130	1.745