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



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# for mid-term sustainable supply chain network design

**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.

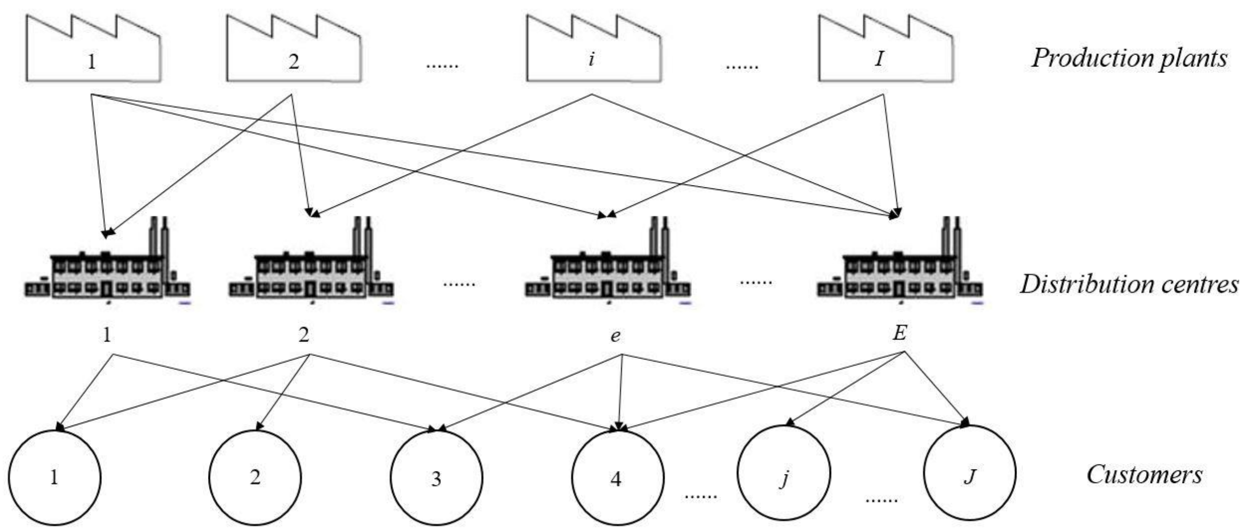



**Figure 1.** Schematic of the production and distribution supply chain network

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 $tonCO_{2-eq}$ and cost in euros;
- ✓ economies of scale affect production costs.

The following notations are introduced and used in the following:

- 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, $t = 1, \dots, T$ |

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

| | |
|---|---|
| $D_{jt}$ | 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 $\left[\frac{€}{\text{ton}\cdot\text{period}}\right]$ |
| $h_j$ | Storage cost at customer warehouses $\left[\frac{€}{\text{ton}\cdot\text{period}}\right]$ |
| $p_{io}$ | 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] |

- Objective functions and bounds

| | |
|---|---|
| $\xi_d$ | Dual objective bound |
| $\xi_p$ | Primal objective bound |
| $\psi^C$ | Production, distribution and storage costs [€] |
| $\psi^G$ | Production, distribution and storage emissions [ton$CO_{2\text{-eq}}$] |
| $\psi^L$ | Stock level at warehouses [ton] |

*3.1 Mid-term optimization model description*

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

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

$$\begin{aligned}\min \psi^G = {} & \sum_{i=1}^{I}\sum_{o=1}^{O}\sum_{t=1}^{T} B_i \cdot z_{iot} + \sum_{i=1}^{I}\sum_{e=1}^{E}\sum_{k=1}^{K}\sum_{t=1}^{T}(B_k \cdot d_{ie} \cdot v_{iekt}) + \sum_{e=1}^{E}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T}(B_k \cdot d_{ej} \cdot v_{ejkt}) \\ & + \sum_{e=1}^{E} B_e \cdot \left(\sum_{t=1}^{T} g_{et} + g_{eT} + \sum_{i=1}^{I}\sum_{k=1}^{K} q_{iekT} - \sum_{j=1}^{J}\sum_{k=1}^{K} q_{ejkT}\right) \\ & + \sum_{j=1}^{J} B_j \cdot \left(\sum_{t=1}^{T} g_{jt} + g_{jT} + \sum_{e=1}^{E}\sum_{k=1}^{K} q_{ejkT} - D_{jT}\right)\end{aligned} \tag{2}$$

$$\begin{aligned}\min \psi^C = {} & \sum_{i=1}^{I}\sum_{o=1}^{O}\sum_{t=1}^{T} p_{io} \cdot z_{iot} + \sum_{i=1}^{I}\sum_{e=1}^{E}\sum_{k=1}^{K}\sum_{t=1}^{T}(c_k \cdot d_{ie} + cfix_k) \cdot v_{iekt} \\ & + \sum_{e=1}^{E}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T}(c_k \cdot d_{ej} + cfix_k) \cdot v_{ejkt} \\ & + \sum_{e=1}^{E}\sum_{t=1}^{T} h_e \cdot g_{et} + \sum_{e=1}^{E}\left(g_{eT} + \sum_{i=1}^{I}\sum_{k=1}^{K} q_{iekT} - \sum_{j=1}^{J}\sum_{k=1}^{K} q_{ejkT}\right) \\ & + \sum_{j=1}^{J}\sum_{t=1}^{T} h_j \cdot g_{jt} + \sum_{j=1}^{J}\left(g_{jT} + \sum_{e=1}^{E}\sum_{k=1}^{K} q_{ejkT} - D_{jT}\right)\end{aligned} \tag{3}$$

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.

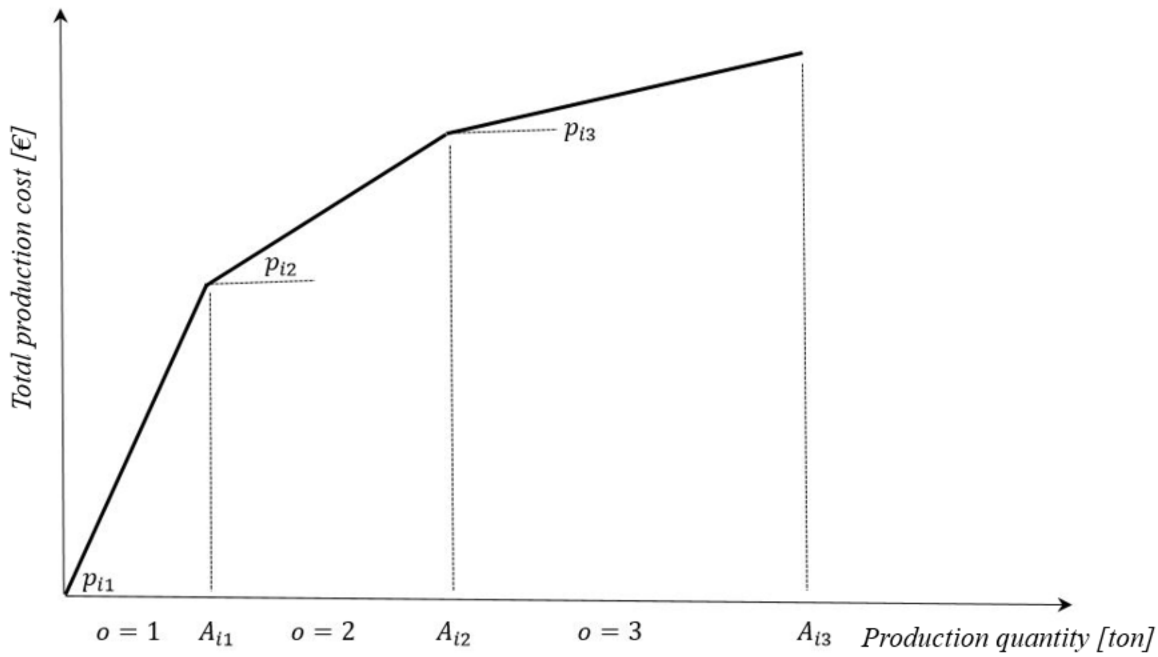



**Figure 2.** Mathematical framework for economies of scale modelling

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:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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.

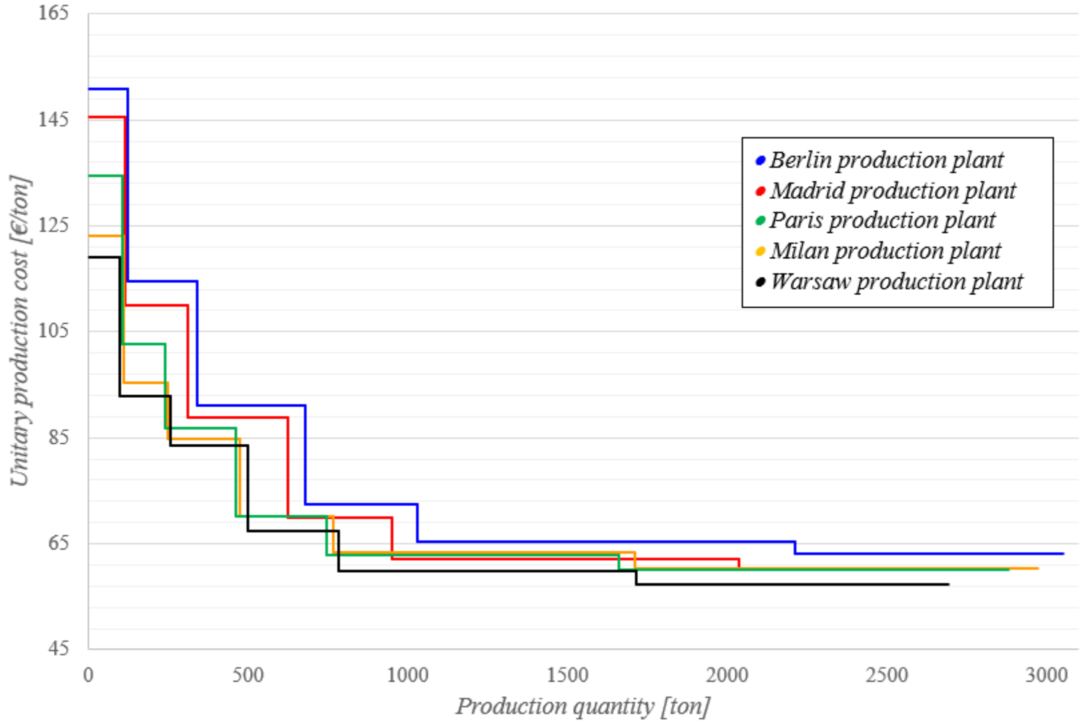



**Figure 4.** Unitary production cost function for the five production plants

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$^{TM}$ 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 $\xi_p$ is the primal objective bound, i.e., the incumbent objective value, which is the upper bound for the minimization problems, and $\xi_d$ 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.

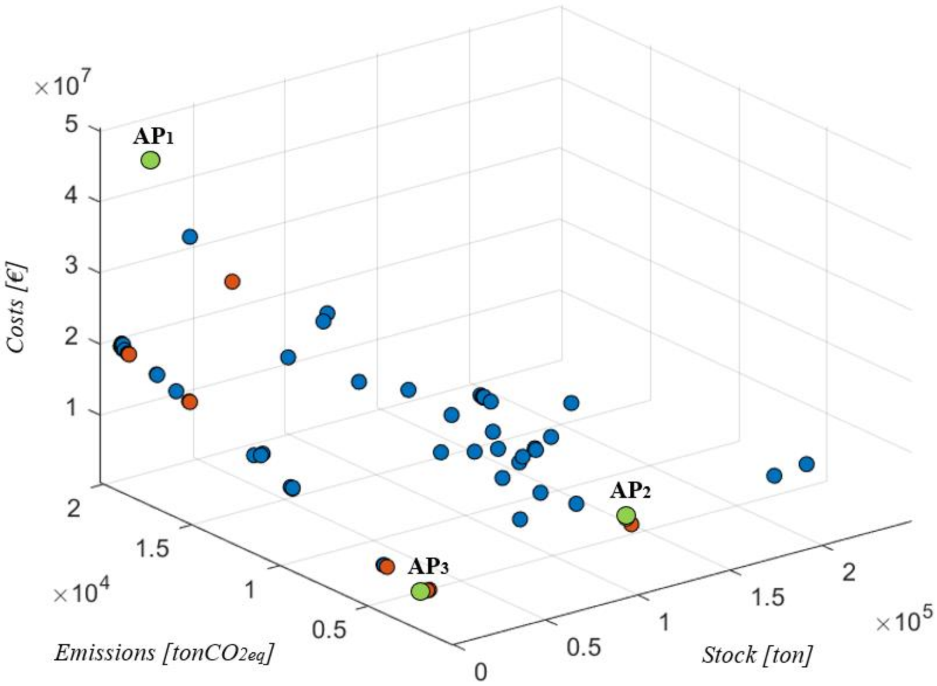



**Figure 5.** Industrial application, solution space

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 ton$CO_{2\text{-eq}}$ 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 ton$CO_{2\text{-eq}}$, 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 ton$CO_{2\text{-eq}}$ 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 [ton$CO_{2\text{-eq}}$] | 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 [ton$CO_{2\text{-eq}}$/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 [ton$CO_{2\text{-eq}}$] | 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, $\gamma_a$, as in Equations (30) to (33).

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

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

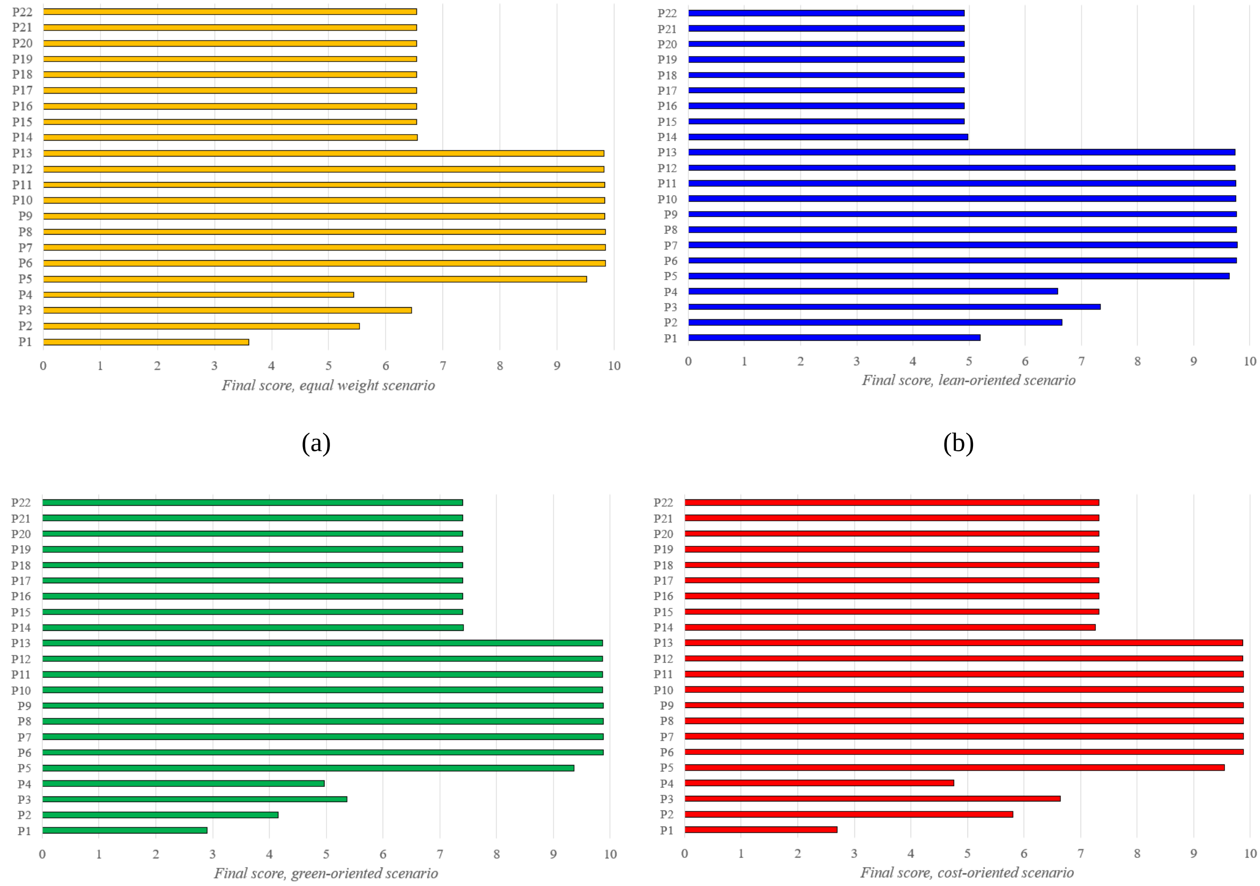
$$\gamma_a^C = 10 \cdot \frac{\max_b\{P_b^C\} - P_a^C}{\max_b\{P_b^C\} - \min_b\{P_b^C\}} \tag{32}$$

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

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 $\delta^F$ 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, $\gamma_a^L$, green, $\gamma_a^G$, and cost, $\gamma_a^C$. 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 ($\delta^L = 2 \cdot \delta^G = 2 \cdot \delta^C = 1/2$).

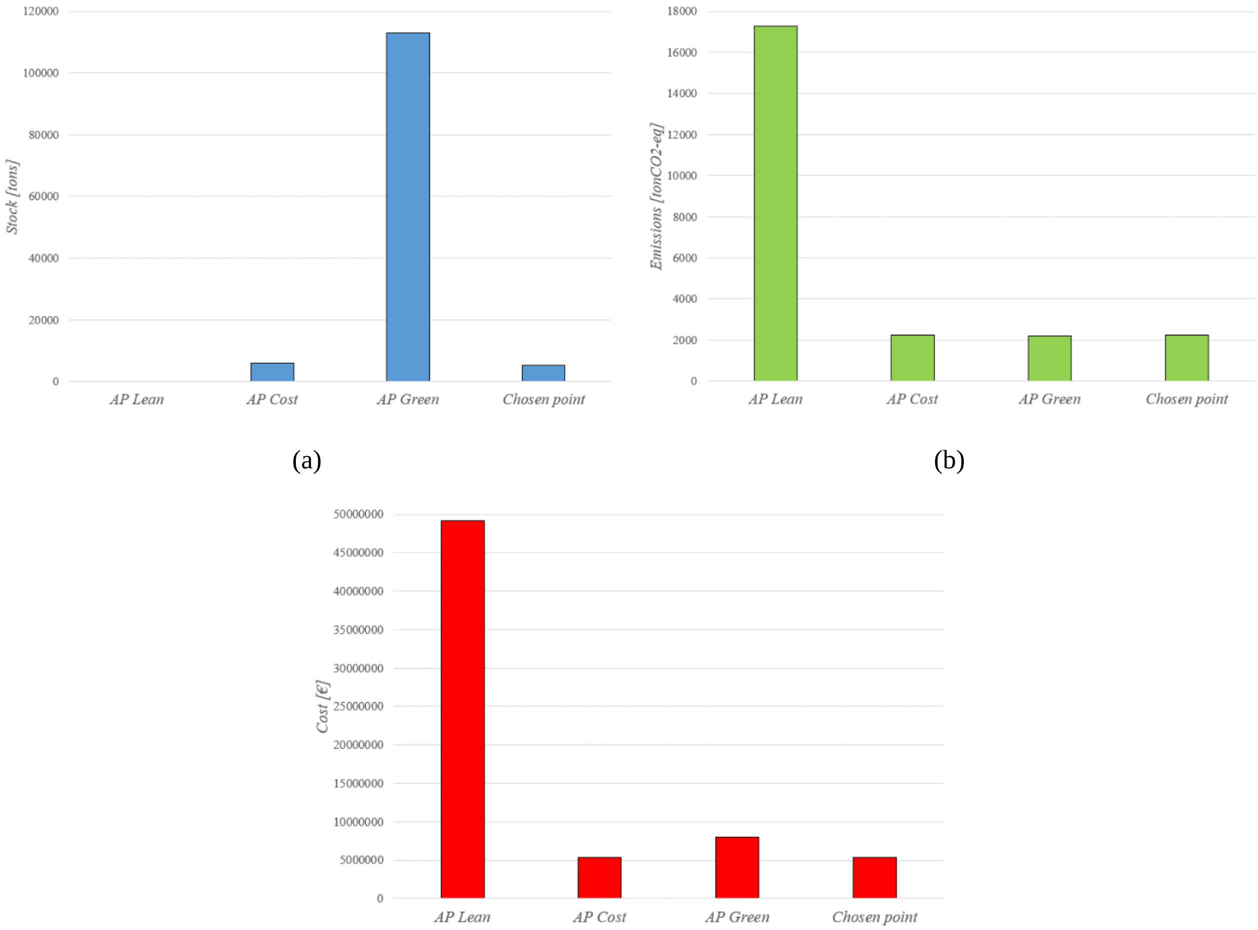



(a) (b)

(c) (d)

**Figure 6.** Pareto point final scores for the four scenarios, (a) - (d)

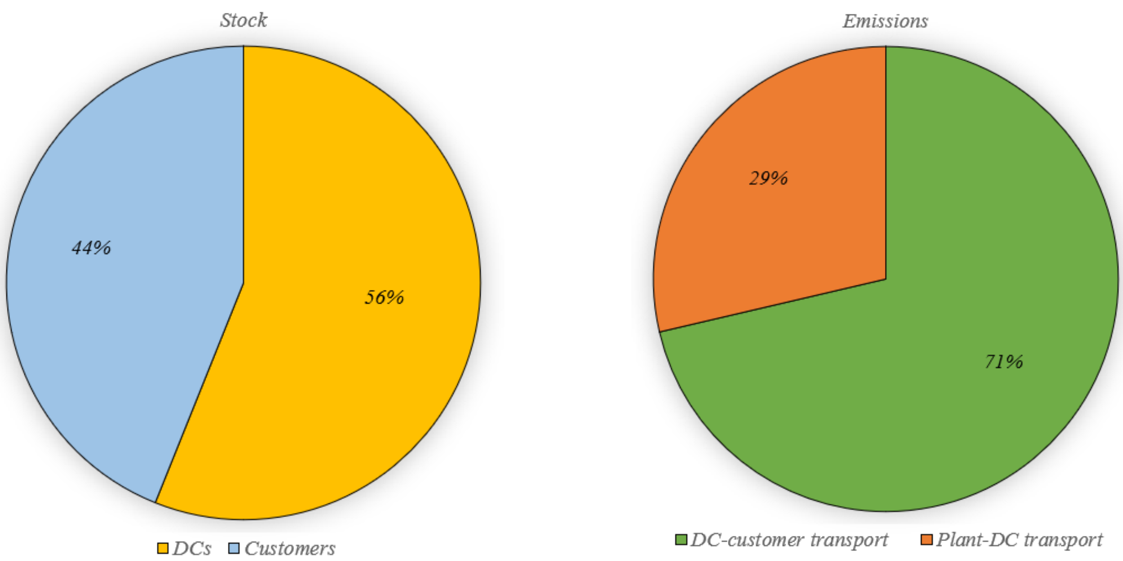
Points from $P_6$ to $P_{13}$ have a final score higher than 9.7 in all the analysed scenarios. These points show a good balance among the three objective functions, presenting acceptable values of stock levels, emissions and global cost. The Pareto point with the higher global score is $P_7$ in all scenarios, presenting a stock level of 5’206 tons, emissions equal to 2’241.70 ton$CO_{2\text{-eq}}$ 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.



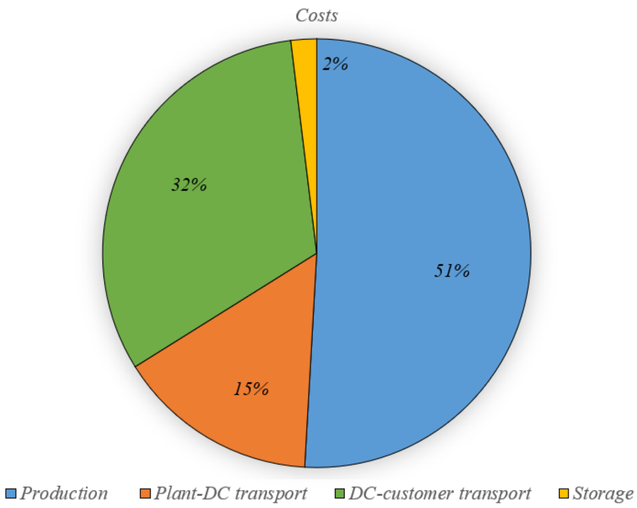

(a) (b)

(c)

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




(a) (b)

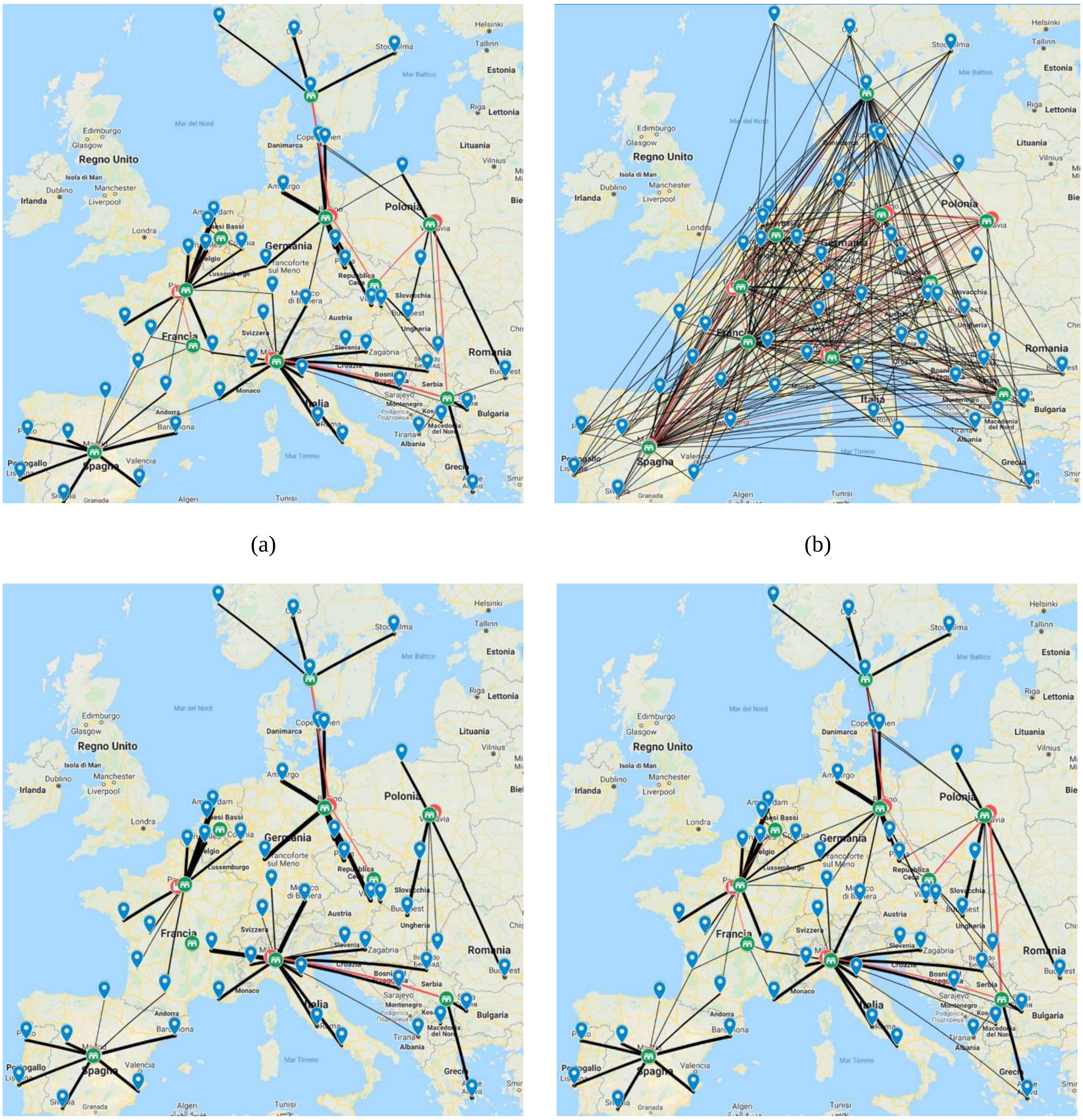



(c)

**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.

| | | | Supply capacity ($A_{io}$) | Production cost ($P_{io}$) |
|---|---|---|---|---|
| Production plant ($i$) | | Zone ($o$) | [ton] | [€/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 |