Resilient food supply chain design: Modelling framework and metaheuristic solution approach

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Abstract

This paper addresses the Resilient Food Supply Chain Design (RFSCD) problem, which is the problem of designing a food supply chain that is resilient enough to ensure business operations continuity in the event of risks or disruptions. Based on a graph theory representation of the food supply chain, this paper proposes a bi-objective mixed-integer programming formulation for this problem. The objectives are to (1) maximize the total profit over a one-year time span and (2) minimize the total lead time of the product along the supply chain. To solve the model, an Ant Colony Optimization (ACO) algorithm is presented. The developed model is suitable for adoption for the design of a multi-product resilient FSC that makes use of a multiple sourcing policy to deal with unexpected fluctuations of market demand and disruptions in raw materials supply. The adapted ACO algorithm is tested on a case study, referring to the SC of readymade UHT tomato sauce, which is particularly vulnerable to such risks.

Keywords: Supply Chain Management; Food Supply Chain Design; Resilient Supply Chain Design; Multiple-sourcing policy; Multi-objective optimization; Ant Colony Optimization.

1 Introduction

The growing complexity of modern supply chains (SCs), together with increasing pressure on efficiency and delivery time, has resulted in increased vulnerabilities. Companies increasingly rely on complex networks of suppliers and partners to deliver product in the right quantities, at the right place, at (just) the right time in a market that is at the same time, however, increasingly fickle. The global SC complexity, the low stock levels, and the limited use of redundancies required to achieve the efficiency targets, do nothing but increase the degree of exposure to a wide range of uncertainties related to risks and SC disruptions (e.g. Lee, Padmanabhan & Whang 1997; Fisher 1997).

It has been shown that companies that have experienced a disruption have achieved a shareholder return that is approximately 30% lower than its competitors (Hendricks & Singhal 2005). Such disruptions can occur in different parts of the supply chain but are often due to problems with the sourcing of critical materials. A well-known example is the reliance on a limited supplier base in the automotive industry, which became apparent after the 2011 Japan earthquake, when many automotive companies experienced supply disruptions (e.g. Matsuo 2015). Next to materials not being available, disruptions can also be caused by quality problems, especially in industries like the food industry, where the dispersion of quality problems throughout the chain can lead to major health concerns and expensive product recalls. Well-known examples are the 2008 melamine contamination in the Chinese dairy industry, leading to more than 300,000 victims (e.g. Marucheck et al. 2011), as well as the 2009 salmonella contamination in peanut butter that lead to a recall involving 361 companies and 3,913 products (Andrews 2012; CDC 2009).

Since there are so many disruption risks that may threaten SC operations, being able to develop resilience may be a real competitive advantage. In this context, companies are incentivized to invest in their future by designing resilient supply chains, dedicating effort and resources in business continuity plans to face the economic and environmental turbulence. Christopher & Peck (2004) defined the resilience of a SC as "the ability of a SC to both respond quickly to disruptions and unforeseen events and to recover operational capability after disruptions occur", thus referring to the ability of a SC to return to its original state or continue operations within a disrupted SC. As such, resilience should be considered in supply chain design (SCD): selecting the right resources to carry out SC operations, also when experiencing disruptions, is crucial (Coutu 2002; Schmitt & Singh 2012).

This paper specifically focuses on food supply chains (FSCs), i.e. SCs that operates in the food industry and extend from individual farmers and/or breeders to the final consumers, covering the entire "farm to fork" process. The design of these FSCs depends on many product characteristics, as well as size and market power of the FSC members (Maloni & Brown 2006). A high density of embedded players and relationships between them adds complexity to FSC network analysis and design problems. Also, many challenges related to food quality, food safety, and sustainability add additional complexities (e.g. Akkerman et al. 2010; Wang et al., 2019). Unfortunately, the growing complexity of modern FSCs usually runs in parallel with an increasing vulnerability.

For FSCs, researchers have noted several trends related to increased risk and resilience problems. In general, the increasing world population and its urbanization has increased the attention in securing food supply (e.g. Tendall et al, 2015; Wang, 2019). In reaction to these discussions on achieving food security on a regional, national, or even global level, food supply chain management has increasingly emphasized resilience (e.g. Zhao et al., 2017; Stone & Rahimifard, 2018). In parallel, the food industry has also witnessed the adoption of lean and just-in-time practices and related decreases in inventory levels. This however increases the impact of possible disruptions. This is even more the case in an industry where inventory buffering is already limited due to product perishability. Furthermore, there is a reduction in control over the different processing stages due to the globalization of SCs and a related difficulty in allocating resources for risk mitigation based on the probabilities that the risk will materialize (Roth et al. 2008). Therefore, modern FSCs are among the most vulnerable and fragile, since any disruption occurrence would rapidly interrupt the operations of the entire network. In addition, any risk that may occur especially in critical food materials supply could have terrible consequences on health and safety aspects and arguably affect final customers even more than the FSC itself.

Despite the importance of these issues for FSCs, there are no existing studies in the literature that specifically deal with resilient FSC design (RFSCD). This paper therefore aims to provide a modelling and solution approach to support RFSCD decision making. More specifically, the contributions of this paper are (1) the introduction of a generic graph representation of the RFSCD problem, (2) the formulation of the RFSCD as a bi-objective optimization model, and (3) the development of a metaheuristic approach based on adapted ant colony optimization (ACO) to solve the RFSCD problem. This modelling framework and solution approach were chosen because of its intuitive nature and the characteristic of ACO that makes explicit use of elements of previous solutions in developing new ones (Maniezzo et al. 2004). This feature can be useful when dealing with resilience, as the purpose of RFSCD is to reconfigure the system in the case of disruption without worsening the system's performance compared to the original configuration. Moreover, several studies have highlighted the effectiveness of ACO algorithms in solving multi-objective optimization problems in general (e.g. Chaharsooghi & Kermani 2008) and problems where path between nodes in a graph should be delineated in particular (e.g. De Santis et al. 2018).

This paper illustrates and tests the proposed approach in a case study of a supply chain for readymade UHT tomato sauce. The application shows that the proposed algorithm is effective in supporting RFSCD, as it is able to identify an efficient configuration of the system in the case of disruption.

The remainder of this paper is organized as follows. Section 2 reviews the literature related to resilient SC design and optimization problems. Section 3 describes the problem setting in more detail, followed by the graph representation, optimization model, and ACO-based algorithm in Section 4. Section 5 details the application of the algorithm in a case study on UHT readymade tomato sauce SC. Finally, Section 6 concludes by summarizing the main finding of the study, discussing the main implications and outlining future research directions.

2 Related literature

Several streams of literature are relevant in relation to the topic of this paper. First, there is extensive literature on the concepts of risk and resilience, based on which different risk categories are briefly discussed. Subsequently, the main developments in the SCD literature related to modelling approaches and solution methods are discussed.

2.1 Risk and resilience

There are various interpretations of the concept of risk in literature. This paper links the concept to that of SC vulnerability: a SC is said to be "at risk" (and therefore "vulnerable") when it is "likely to be lost or damaged” because of uncertain events, causing serious economic losses (Christopher & Peck 2004).

SC risks can be categorized into many different ways and from different perspectives. Referring to the framework of Mason-Jones & Towill (1998), Christopher & Peck (2004) distinguish between internal and external risks. For the external risk, they further distinguish demand risks, supply risks, and environmental risks. Here the first two are present within supply chains, and the third is present outside the supply chain (e.g. socio-political, economic, or weather-related events). In relation to SCD, the impact of external risks on the supply chain network structures is often a key challenge.

Looking at their nature, uncertainties and risks in the SC may occur in three broad forms, known as deviations, disruptions, and disasters (Gaonkar & Viswanadham 2004). A deviation is assumed to occur when one or more parameters (such as cost, demand, lead-time, etc.) within the SC system stray from their expected or mean value, without any change to the underlying SC structure. A disruption occurs when the structure of the SC system is radically transformed, due to unexpected events caused by human or natural factors; resulting in the unavailability of certain production, warehousing and distribution facilities or transportation options. Finally, a disaster is defined as a temporary irrecoverable shut-down of the SC network due to unforeseen catastrophic system-wide disruptions. Among these three forms, SC practitioners and researchers have mostly studied SC deviations and disruptions.

2.2 Food supply chain design

When using mathematical programming, the SCD problem is typically represented by mathematical models based on facility location and allocation decisions. The advantage of using mathematical modelling is the possibility to find the optimum solution to the problem; conversely, the main disadvantage is that for larger problems, the computation time increases rapidly (in the worst case, exponentially) with the problem size. Many approaches exist in the literature, and for a more comprehensive overview of research in this direction, interested readers are referred to Melo et al. (2009) and to more recent SCD reviews focused on disruptions by Snyder et al. (2016) and on including uncertainties by Govindan et al. (2017). As this paper focuses on food supply chains, the remainder of this section specifically discusses strategic SCD approaches in food contexts.

An overview of food SCD approaches was presented some years ago by Akkerman et al. (2010). For strategic SCD problems, they mostly find mathematical programming approaches, complemented with some simulation studies and heuristic approaches. Since the publication of their overview, food SCD has received significant attention. To elaborate on recent developments, Table 1 provides an overview of relevant recent research. As can be seen in the table, most of the recent literature has continued to use mathematical programming approaches, sometimes in combination with (meta)heuristic solution approaches to be able to deal with larger problem instances. A more detailed discussion on solution approaches and the use of metaheuristics is included in the next section of this paper.

Demonstrated by Table 1, a clear development is that many of the recent approaches focus on multiple objectives. In most cases, this is due to the increasing relevance of sustainability indicators. In most of these studies, environmental performance measures (e.g. emissions) are considered in addition to the traditional economic performance measures (e.g. costs). In a limited number of studies, food quality aspects or social indicators are also considered. Resilience is however hardly addressed. The only exception is part of the work presented by Validi et al. (2014). In their scenario analysis, these authors discuss the costs of opening additional (redundant) transportation links in their distributon network, which is argued to represent an increased network resilience. Outside of this implicit consideration of resilience, none of the supply chain design approaches in the literature explicitly consider resilience, despite its increasing relevance.

Table 1: Overview of recent literature on food supply chain design.

Reference	Product	Method	Objectives	Objectives / features
Khamjan et al. (2013)	Sugar cane	MIP + decomposition heuristic	Single	Cost minimization including investment, transportation, as well as yield losses. Applied in case study in Thailand.
Soysal et al. (2014)	Beef	MIP	Multiple	Multi-objective approach (economic and environmental). General approach with case application focusing on interactions between costs and emissions.
Validi et al. (2014)	Dairy	MIP + metaheuristic	Multiple	Multi-objective approach (economic and environmental). Focus on distribution routes and vehicle choice. Some consideration of resilience in scenario analysis.
Van der Vorst et al. (2014)	General	Discrete event simulation	Multiple	Development of generic simulation environment with case illustration. Focus on including food quality in supply chain simulation modelling.
Etemadnia et al. (2015)	Fruit and vegetables	MIP + heuristic	Single	Cost minimization in a national supply chain to distribute food and vegetables. Emphasis on hub locations and transportation modes, as well as localization of food supply.
An and Ouyang (2016)	Grain	MIP + game theory	Single	Bi-level robust optimization approach considering profit maximization and uncertain crop yields. Interaction between food company and farmers captured in Stackelberg game.
Mohammed and Wang (2017a;2017b)	Meat	MIP	Multiple	Multi-objective approach (two transport aspects and delivery time) considering uncertainty in a variety of parameters.
De Keizer et al. (2017)	General	MIP	Single	Profit-maximization approach with allocation of storage and processing activities in a network. Emphasis on product quality deterioration. General approach with case illustration.
Soto-Silva et al. (2017)	Apple	MIP	Multiple	Combination of model for purchasing and model for storage and transportation, leading to bi-objective model (two different cost functions).
Musavi and Bozorgi-Amiri (2017)	General	MIP + metaheuristic	Multiple	Multi-objective approach (economic, environmental, and quality indicators) to a location-routing problem. Development of genetic algorithm to solve the problem.
Miranda-Ackerman et al. (2017)	Orange juice	MIP + metaheuristic + MCDM	Multiple	Multi-objective approach (economic and environmental objectives) solved with genetic algorithm. Subsequent use of multi-criteria decision making (MCDM) to select between Pareto-optimal solutions.
Varsei and Polyakovskiy (2017)	Wine	MIP	Multiple	Multi-objective approach (economic, environmental, and social objectives) solved with augmented epsilon constraint method. Emphasis on analyzing interactions between the objectives.
Mogale et al. (2017a;2017b;2018)	Grain	MINLP + metaheuristic	Single	Cost minimization in a national supply chain to distribute grain. Emphasis on food security and seasonal production.
Allaoui et al. (2018)	General	MCDM + MIP	Multiple	Multi-criteria decision making (MCDM) to select supply chain partners, followed by multi-objective optimization for network design (various economic, environmental, and social objectives).

Martins et al. (2019)	General	MIP	Multiple	Lexicographic multi-objective approach (economic, environmental, and social objectives) for food bank networks. Emphasis on capacity decisions.

2.3 Solution approaches

As an alternative to mathematical programming approaches, metaheuristics are often developed to solve SCD problems. Recent work also found that the use of metaheuristics is significantly growing in time, especially for complex SCD problems, for which analytic models could be ineffective (Mogale et al., 2017a). This section therefore gives an overview of relevant solution approaches.

Compared to the traditional optimization methodologies, metaheuristics do not guarantee that a globally optimal solution can be reached, but they allow for reasonable solutions within acceptable time. However, many logistics and SC problems are too large or too complex for traditional optimization methods to guarantee an optimal solution, while metaheuristics are often able to find near-optimal solutions in a reasonable amount of time. In addition to size and complexity arguments, metaheuristics provide a robust method that can be adapted to problems with different solution characteristics. This feature can be very helpful to face SC problems, constraints, and conditions that may change frequently. The structure of metaheuristic algorithms also makes them easy to update and re-run when changes occur (Lourenço 2005). However, also metaheuristics have their disadvantages. Establishing control or tuning parameters can increase the difficulty of metaheuristic algorithms, because the choice does not depend on a specific method, and sometimes various attempts have to be made using different parameter values. In the context of SCs, metaheuristics are however used for many typical problems, such as *vehicle routing* (Shyu, Lin & Yin 2004; Reimann & Laumanns 2006; Reimann & Ulrich 2006, Tang et al. 2014, Panicker et al., 2013), *production planning* (Bautista & Pereira 2007), *job sequencing* (McMullen, 2001) and *product design* (Albritton & McMullen, 2007); moreover, they have shown a great effectiveness of solving SCD problems.

A widely used metaheuristic is the genetic algorithm (GA). For instance, Altiparmak et al. (2006) proposed a solution procedure based on a GA to find the set of Pareto-optimal solutions for multi-objective SCD problem. They designed a four-echelon SC (suppliers, plants, warehouses, and customers) trying to optimize simultaneously the costs, the orders fulfilment within the due dates, and the capacity utilization for plants and warehouses. Costa et al. (2010) also used a GA with a new chromosome encoding and a complementary decoding procedure, able to overcome the drawbacks and thus improve the efficiency and effectiveness of three-stage SCs. They minimized the total logistic cost resulting from the transportation of goods and the location and opening of the facilities. Pinto (2004) used a multi-objective GA to solve a Pareto optimality problem of designing a single-product three-stages SC; the study makes use of the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) developed by Deb et al. (2002). Another example is the work by Serrano et al. (2007), who propose an NSGA-II algorithm to mitigate the SC risks and to design a SC that is resilient enough to respond to a specific disruption in production.

In addition to GAs, other metaheuristics have also been applied to SCD. For instance, Cardona-Valdès et al. (2014) applied a bi-objective tabu-search algorithm for the design of a two-echelon production-distribution network with multiple manufacturing plants, distribution centres, and a set of candidate warehouses. Chibeles-Martins et al. (2014) explored alternative strategies for the local search mechanism of a bi-objective simulated annealing algorithm. Swarm intelligence algorithms have also been applied to the general SCD problem, showing good effectiveness. For instance, Silva et al. (2004) considered an SC composed of three sub-systems: a logistic sub-system, a supplying sub-system and a distribution sub-system. The authors adopted an ant colony optimization (ACO) algorithm that showed a great effectiveness in finding a satisfactory SC configuration. Moncayo-Martinez and Zhang (2011) proposed an algorithm based on Pareto ant colony optimization (P-ACO) as an effective metaheuristic method for solving multi-objective SCD problems. More recently, Moncayo-Martinez (2015) presented an improved ACO-based algorithm, called rank-based ant system to solve a bi-objective SCD problem.

As this summary shows, metaheuristic algorithms (and swarm-based algorithms in particular) appear as a class of suitable tools to solve SC design problems; they have been used in several studies reviewed. ACO algorithms, in particular, emerged as one of the best-suited metaheuristics to multi-objective optimization and SCD problems. However, despite this fact, none of the studies reviewed has also taken into account resilience aspects, in terms of the disruption risks that may occur in a SC. Consequently, there are no existing studies that provide an effective swarm-based algorithm suitable to be adopted to design a resilient FSC, which is therefore the focus of this study. Hence, this paper extends the use of swarm intelligence algorithms to the issue of resilient FSCD in which disruptions might occur. This paper also aims to contribute to the literature by proposing a model suitable to be used in the case of a multi-echelon, multi-product FSC, subject to different supply disruption scenarios and demand variability.

3 Resilient food supply chain design

The purpose of RFSCD is to find an effective and efficient design of an FSC, while ensuring resilience to maintain operational continuity in major supply disruptions scenarios and in presence of demand variability. An FSC consists of a large number of players that are connected to and embedded in the network around them. Starting from raw materials suppliers, food products flow through different processing and distribution stages or activities. Also, these activities can often be performed by different actors or in different ways, leading to a selection process with different options for each activity at the core of the RFSCD problem.

Furthermore, an aspect related to the resilience of supply is that suppliers can often be categorized based on their criticality. This paper distinguishes between *critical* and *non-critical* supply. A *critical* supply relates to the major raw materials, i.e. food ingredients whose quality directly affects final food product quality, whereas *non-critical* supply relates to minor raw materials or services, which have less impact on the final food product quality (e.g. additives, packaging, or logistics support services). Finally, for the critical supply, a further distinction is made between *high-quality* and *low-quality* suppliers.

An FSC is defined univocally by the set of its activities, by the (supply-demand) relationships between them, and by the specific food product or food product mix offered to internal and/or external markets. Therefore, the essential data required to describe an FSC consist of four elements, namely:

- The food products type and characteristics;
- the number and the type of players (activities) and their criticality;
- the supply-demand relationships between these activities;
- the number of options available to perform each activity.

More specifically, FSC activities can be organized into 3 groups (illustrated in Figure 1):

1. A *food supply* stage, which includes all suppliers (here, options represent different suppliers that can supply the same component/raw material);
2. A *food processing* stage, which includes all the processing plants and transformation activities (here, options represent different manufacturing plants or different production lines in which an intermediate or final food product could be processed);
3. A *food distribution* stage, which includes distribution centres, retailers, and delivery activities (here, options represent different ways of delivering a food product to distribution centers, retailers, retailer, and other marketplaces).

The determination of the best SCD implies the selection of supply options, processing options, and delivery options across the FSC to optimize the performance of the network. The resilience of the SCD has to be included in the selection of options, in which the quality differentiation for the options of critical supply activities also adds a quality dimension to the trade-off between risks and supply chain performance. In this paper, two common objective functions are used simultaneously: total costs and total lead time, allowing for a comprehensive evaluation of the SC performance.

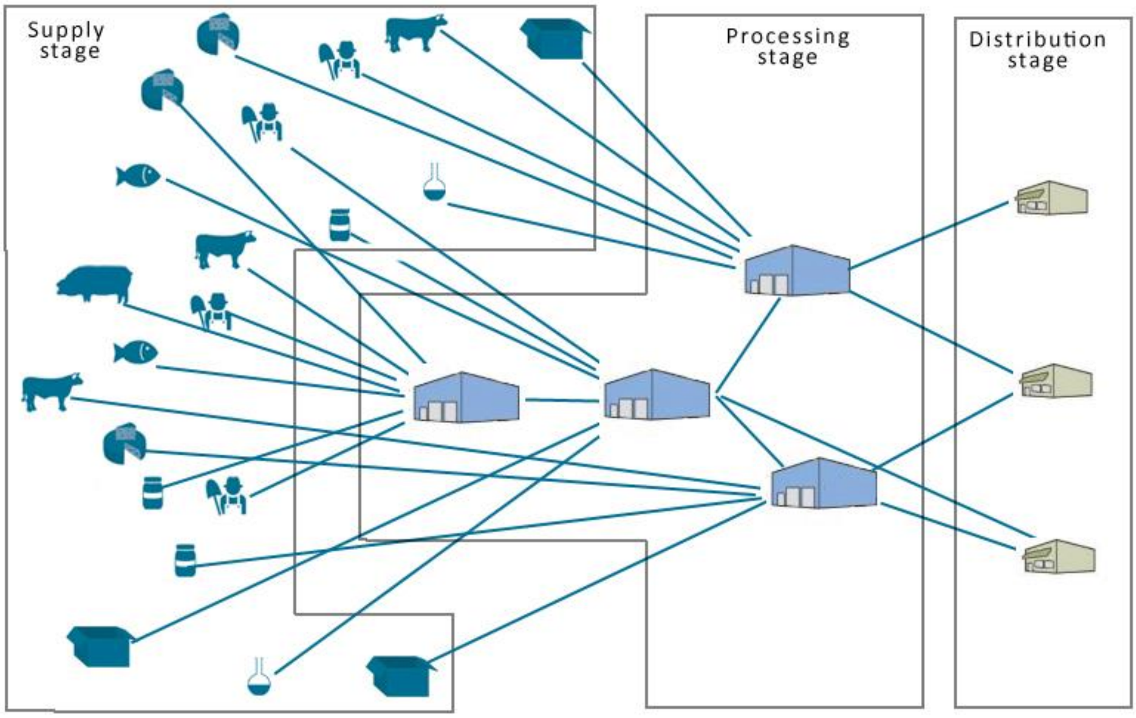

Figure 1: An illustrative FSC.

4 Modelling framework and solution approach

In this section, the modelling approach is described, starting with the graph representation of the RFSCD problem in Section 4.1, followed by the formulation of a bi-objective non-linear optimization model in Section 4.2. Afterwards, Section 4.3 outlines the adapted ACO algorithm proposed to solve the problem.

4.1 Graph representation

To be able to describe the SCD problem and the solution approach formally, the FSC is represented in the form of a two-level weighted graph. Graph theory is a common representation in SCD problems (Moncayo-Martìnez & Zhang, 2013; Mogale et al., 2017a) and in ACO-based algorithms in particular, as in the original formulation of the ACO algorithm ants are modelled as entities that move from one node to another through arcs that connect those nodes (Dorigo & Stützle, 2004).

According to the notation Table 1, primary activity nodes correspond to a specific FSC activity $v_i^r \in V$, where i represents the activity and r the activity type, which can encompass three subsets of activities (supply activities, processing activities, and distribution activities).

Table 1: Notation used in the graph representation.

Superscripts	Description
r	activity type ($r = s$ for supply, $r = p$ for production, $r = d$ for delivery)
CR, NCR	critical, non-critical
HQ, LQ	high-quality, low-quality

Subscripts	Description
i	FSC activity ($i = 1, \dots N$), $N = N_s + N_p + N_d$, $N_r \subset N\ \forall r$, $N_r^{CR} + N_r^{NCR} = N_r\ \forall r$
j	option of an activity ($j = 1 \dots J_i$)
Parameter	**Description**
V	Set of primary activity-nodes of the FSC, with subsets $V_r \subset V\ \forall r$ and $V_s + V_p + V_d = V$
$v_i^r \in V$	Primary activity node representing the i^{th} activity type r
W_i	Set of nodes including all options to perform the i^{th} activity, $W_i^{HQ} \subset W_i$, $W_i^{LQ} \subset W_i$ and $W_i = W_i^{HQ} + W_i^{LQ}$
$w_{ij}^r \in W_i$	Secondary activity node representing the j^{th} option to perform the i^{th} activity type r
$CAPmax_{ij}^r$	Maximum capacity of w_{ij}^r [kg/month]
CAP_{ijt}^r	Capacity of w_{ij}^r at time t [kg/month]
c_{ij}^r	Cost of the j^{th} option for the i^{th} activity type r [€/kg]
t_{ij}^r	Lead time of j^{th} option for the i^{th} activity type r [days]
π_{ij}^s	Disruption probability of j^{th} option for the i^{th} supply activity [%]
A	Set of arcs, i.e. possible supply-demand relationships between activity-nodes, consisting of node pairs $(v_i^r, v_{i'}^r) \in V$ with possible combinations $i \in I_s \wedge i' \in I_p, i \in I_p \wedge i' \in I_p, i \in I_p \wedge i' \in I_d$

Then, since each primary activity-node v_i^r has $j \in J_i$ options to be performed, secondary activity nodes w_{ij}^r are introduced to represent these options, combined in a set W_i of all options available for activity i. To distinguish the high-quality options from the low-quality options for the critical supply activities, subsets $W_i^{HQ} \subset W_i$ and $W_i^{LQ} \subset W_i$ are used.

The set of arcs in the graph representation shows the supply-demand relationships among the activity-nodes. There can be relationships between supply and processing activities, between two processing activities, and between processing and distribution activities.

To illustrate the graph representation, Figure 2 shows a scheme of an FSC network. This example contains four critical primary activity nodes representing supply, each containing some high-quality and low-quality options represented with the secondary activity nodes. The example further contains three non-critical primary activity nodes for supply activities, four for processing activities, and four for distribution activities. Each primary activity node also has two or three secondary activity nodes representing the different options available to perform these activities.

Finally, weights are associated to each of the secondary activity nodes of the graph to describe the characteristics of the specific activity option that is represented. More specifically, each node w_{ij}^r has its own activation and utilization cost c_{ij}, a processing lead time t_{ij} and a maximum production capacity CAP_{ij}. Moreover, in order to be able to evaluate different supply disruption scenarios, each secondary supply activity node v_{ij}^s has a disruption probability value π_{ij} that must be estimated from historical disruption data. This paper does not further elaborate on this, but it should be noted that it might be useful to use conservative (i.e. not too low) estimates of the disruption probabilities.

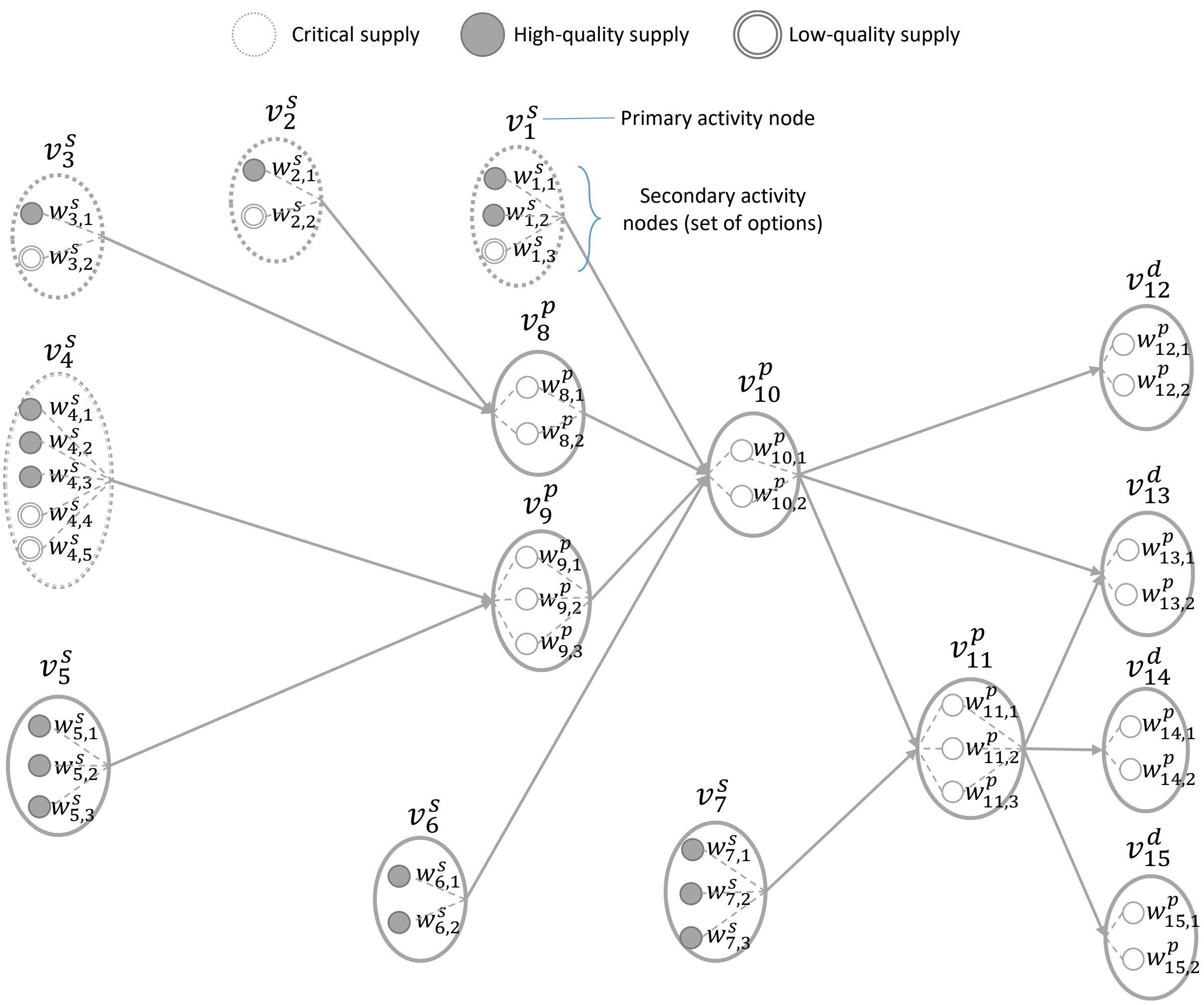

Figure 2: An example of a FSC representation by graph.

4.2 Mathematical model formulation

To formulate the mathematical model, the additional notation outlined in Table 2 is used. The model aims to capture the RFSCD problem described above and is based on the assumptions described below.

1. The market demand must be fully satisfied in each period t over a one-year time horizon;
2. Food products are distributed to different markets from delivery nodes, while the other primary activity nodes have internal customers only;
3. The selling price for the k^{th} product is known and depends on the quality level of the critical raw materials supplied;
4. The demand for the k^{th} product is normally distributed across the different periods and i.i.d. The average demand value is assumed fixed at each period t to account for $\mu_{kt} \equiv D_{kt}$;
5. For any period t, the average demand value at each internal primary activity node is the sum of the average demand values of its downstream activity nodes;
6. Every secondary activity node (i.e. every option) has a fixed maximum production capacity;

7. A multiple sourcing policy is assumed. In any period t, if the best available option selected to perform a primary activity is not able to satisfy the total demand at that primary activity node, a further activity option must be added. This operation is repeated until the demand is fully satisfied;
8. Lead times are deterministic;
9. The total lead time (TLT) of the supply chain is obtained as the maximum time-to-market of the product.

Table 2: Notation used in the mathematical model formulation.

Index, parameter, or variable	**Description**
k	Food products ($k = 1, \dots K$)
t	Time horizon ($t = 1, \dots T$)
ε	Weighting objective factor assigned to Total Profit ($0 < \varepsilon \leq 1$)
ω	Weighting objective factor assigned to Total Lead Time ($0 < \omega \leq 1$; $\omega = 1 - \varepsilon$)
$p(y_{ij}^r)_k$	Sales price of the k^{th}product using w_{ij}^r option
p_k^{HQ}	Sales price of the k^{th} product type HQ [€/kg]
p_k^{LQ}	Sales price of the k^{th} product type LQ [€/kg]
D_{ikt}^d	Average demand value of the k^{th} product at the i^{th} delivery activity at time t [kg/month]
μ_{ijkt}	Quota of the k^{th} product demand satisfied by w_{ij}^r at time t [kg/month]
LT_{ij}	Lead time of option $j^{th}$of activity i^{th} [days]
LT_{ij}^d	Lead time of option $j^{th}$of delivery activity i^{th} [days]
y_{ij}^r	Binary decision variable assigned to w_{ij}^r
LL_{TLT}	Lower limit of the total lead time
UL_{TP}	Upper limit of the total profit

Taking into account the assumptions above, the RFSCD problem can be formulated as a bi-objective non-linear mixed-integer model, with two conflicting objectives. Indeed, in presence of supply disruption, the supply chain must be able to reconfigure its structure by resorting to alternative suppliers, with the purpose of minimising the additional lead time this reconfiguration could involve. At the same time, the recourse to alternative suppliers should ensure that the market demand is fully satisfied and that the maximum supply chain profit can be generated.

In line with these considerations, a bi-objective optimization problem, with objective functions $z_1$and z_2, can be formulated in terms of the total profit (TP) and the total lead time (TLT) of the supply chain, as follows:

$$\begin{cases} min\ z_1 = min\ TLT \\ max\ z_2 = max\ TP \end{cases} \tag{1}$$

where:

$$TP = \sum_{k=1}^{K} \sum_{i=1}^{N_d} \sum_{t=1}^{T} p\left(y_{ij}\right)_k D_{ikt}^d - \sum_r \sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{i=1}^{N} \sum_{j=1}^{J_i} \mu_{ijkt} \cdot c_{ij}^r \cdot y_{ij}^r \tag{1a}$$

$$TLT = \sum_{i=1}^{N} \max_{j \in J_i} (LT_{ij} \cdot y_{ij}^r) \tag{1b}$$

subject to:

$$\sum_{j=1}^{J_i} \mu_{ijkt} \cdot y_{ij}^d = D_{ikt}^d \qquad \forall k,t \tag{2}$$

$$\sum_{j=1}^{J_i} \mu_{ijkt} \cdot y_{ij}^r = \sum_{i':\exists(i,i')\in A} \sum_{j'=1}^{J_i} \mu_{i'j'kt} \cdot y_{i'j'}^r \qquad \forall k,t,r;\ i = 1 \dots N_s \wedge i' = 1 \dots N_p \tag{3}$$

$$\sum_{k=1}^{K} \mu_{ijkt} \cdot y_{ij}^r \leq CAPmax_{ij}^r \qquad \forall i,j,r \tag{4}$$

$$p\left(y_{ij}^r\right)_k = \begin{cases} p'_k < p_k & if\ \sum_{i=1}^{N_s^{CR}} \sum_{j=1}^{J_i^{LQ}} y_{ij} \geq 1 \\ p_k & otherwise \end{cases} \qquad \forall k,r \tag{5}$$

$$y_{ij}^r = \begin{cases} 1 & if\ w_{ij}^r\ is\ selected \\ 0 & otherwise \end{cases} \qquad \forall i,r,j = 1, \dots J_i \tag{6}$$

It should be mentioned that selecting option node w_{ij}^r does not necessarily mean that w_{ij}^r is activated at its maximum capacity, in line with the fact that more options can be activated in the same node (see assumption #7 above). In this formulation, TP is computed as the difference between the total revenue from the sale of the finished product (TR) and the cost of goods sold ($COGS$) by the FSC over the time horizon (eq.1a). In turn, TR equals to the sum of the price $p(y_{ij}^r)_k$ of each product k^{th} multiplied by its average demand D_{ikt}^d seen at each period t at each delivery activity-node. Note that the selling price $p(y_{ij}^r)_k$ for the k^{th} food product is expressed as a function of the selected options type at each critical supplying activity-node, as shown in constraint (5). To be more precise, the k^{th} product price equals p_k (the c price level) if all the selected options at any critical supplying activity are of HQ type, while it scores $p'_k < p_k$ (the low-quality price level) if even one selected critical option-supplier is of LQ type. The COGS in eq.1a is expressed as the fraction of the k^{th} product demand per unit time satisfied by the j^{th} option of the i^{th} activity and the cost of the j^{th} option at the i^{th} activity. y_{ij}^r is a decision variable that scores 1 if option j is selected to perform the activity i and 0 otherwise, as expressed in constraint (6).

Constraint (2) ensures that, for each period t, the market demand is fully satisfied at all delivery nodes. Constraint (3) ensures that the average demand per unit time at any activity-node is obtained as the sum of average demands per unit time of the downstream activities linked to it. Constraint (4) ensures that the demand value satisfied by every selected option for all the activity nodes does not exceed the maximum production capacities.

TLT (eq.1b) is the computed by adding up the maximum lead time of each node, in line with the fact that an activity at a particular node cannot start until all required inputs are available at the node (i.e. until all preceding activities are completed).

Using an alternative formulation, the bi-objective optimization problem can be integrated into a single-objective problem using the weighted-sum method, obtaining the following expression:

$$min\ z = \ min\{\varepsilon \cdot (e_{TP}) + \omega \cdot (e_{TLT})\} \tag{1*}$$

where:

$$e_{TLT} = \frac{|TLT - LL_{TLT}|}{LL_{TLT}} \cdot 100 \tag{1a*}$$

$$e_{TP} = \frac{|TP - UL_{TP}|}{UL_{TP}} \cdot 100 \tag{1b*}$$

Constraints (2)-(6) still hold true in this formulation of the problem. The objective function (1*) is expressed as the weighted sum of the total profit and the total lead time through the weighting factors ε and ω. Since TP and TLT are two inhomogeneous quantities, they are normalized into percentage values (e_{TLT} and e_{TP}) as expressed in (1a*) and (1b*). These terms defines the distance between the results returned of the FSCD (TP and TLT) and their upper and lower limits, representing the situation of an FSC operating without disruptions. To be more precise, the LL_{TLT} can be computed by adding up the minimum lead time of each node, while the UL_{TP} is the profit resulting if the supply chain is able to fully satisfy the market demand with high-quality products.

The alternative formulation is useful to derive a synthetic index to evaluate the effectiveness of the solution found; moreover, it allows a different importance to be assigned to the two objectives, thus enabling some sensitivity analyses (cf. section 5.3). Finally, using a single objective is mandatory when solving the problem using linear programming solver; hence, this formulation will be employed to compare the results of the proposed algorithm with those returned by a linear programming solver.

4.3 Adapted ACO algorithm

As discussed earlier, SCD problems tend to lead to large and complex mathematical models, and heuristic procedures are often used to be able to provide decision support approaches that give reasonable solutions within limited time. Furthermore, the choice of developing an ACO-based algorithm reflects the fact that resilient SC characteristics of self-adaptation and self-coordination are well captured by the self-organization features of ant colonies.

In this section, the adapted ACO algorithm developed to solve the RFSCD problem is described. Table 3 contains the additional notation we will use to describe the algorithm.

Table 3: Nomenclature used in the adapted ACO algorithm to solve the RFSCD problem.

Parameter	**Description**
p	ant colonies ($p = 1, \dots P$)
q	ants in a colony ($q = 1, \dots Q$)
α	relative importance of the pheromone trail
β	relative importance of the distance
ρ	pheromone evaporation rate $(0 < \rho < 1)$
τ_{ij}^{r}	Intensity of the pheromone deposited over the j^{th} option of the i^{th} activity type r
$\Delta\tau_{ij}^{r}$	Pheromone increment deposited over the j^{th} option of the i^{th} activity type r
PM	Pheromone Matrix
η_{ij}	Heuristic value
$FSCD_{pq}$	FSCD generated by the q^{th} ant of the p^{th} colony
TP_{pq}	Value of Total Profit at the FSCD generated by the q^{th} ant of the p^{th} colony [€]

TLT_{pq}	Value of Total Lead Time at the FSCD generated by the q^{th} ant of the p^{th} colony [days]
$N_{w_{ij}^{r}}$	Neighbourhood of feasible choices while the current ant is at w_{ij}^{r}
$P_{w_{ij}^{r}}$	Probabilistic decision rule to select the j^{th} option of the i^{th} activity type r [%]

The adapted ACO algorithm starts with the determination of the number of ant colonies P, each consisting of Q ants. Each artificial ant, one after another, tours the entire network producing a FSC design ($FSCD_{pq}$) which is essentially an ordered sequence of option choices made at the activities; formally:

$$
\begin{aligned}
& FSCD_{pq} = \\
& = \{options\ selected\ for\ supply\ nodes\}_{pq} \cup \{options\ selected\ for\ production\ nodes\}_{pq} \\
& \cup \{options\ selected\ for\ delivery\ nodes\}_{pq} \\
& = \left\{\left(w_{11}^{s}y_{11}, w_{12}^{s}y_{12}, \dots w_{1J_1}^{s}y_{1J_1}\right), \left(w_{21}^{s}y_{21}, w_{22}^{s}y_{22}, \dots w_{2J_2}^{s}y_{2J_2}\right), \dots \left(w_{N^s1}^{s}y_{N^s1}, w_{N^s2}^{s}y_{N^s2}, \dots w_{N^sJ_{N^s}}^{s}y_{N^sJ_{N^s}}\right)\right\}_{pq} \\
& \cup \left\{\left(w_{11}^{p}y_{11}, w_{12}^{p}y_{12}, \dots w_{1J_1}^{p}y_{1J_1}\right), \left(w_{21}^{p}y_{21}, w_{22}^{p}y_{22}, \dots w_{2J_2}^{p}y_{2J_2}\right), \dots \left(w_{N^p1}^{p}y_{N^p1}, w_{N^p2}^{p}y_{N^p2}, \dots w_{N^pJ_{N^p}}^{p}y_{N^pJ_{N^p}}\right)\right\}_{pq} \\
& \cup \left\{\left(w_{11}^{d}y_{11}, w_{12}^{d}y_{12}, \dots w_{1J_1}^{d}y_{1J_1}\right), \left(w_{21}^{d}y_{21}, w_{22}^{d}y_{22}, \dots w_{2J_2}^{d}y_{2J_2}\right), \dots \left(w_{N^d1}^{d}y_{N^d1}, w_{N^p2}^{d}y_{N^d2}, \dots w_{N^dJ_{N^d}}^{d}y_{N^dJ_{N^d}}\right)\right\}_{pq}
\end{aligned} \tag{7}
$$

where $\left(w_{11}^{r}y_{11}, w_{12}^{r}y_{12}, \dots w_{1J_1}^{r}y_{1J_1}\right)_{pq}$ denotes, e.g., the ordered subset of secondary activity nodes selected by ant q of colony p to perform the first activity type r.

For artificial ants, the pheromone (τ) must be deposited over the graph which represent the problem. In order to do this, the pheromone matrix (PM) is created. The pheromone τ represents the desirability of the ants to choose each option at each of the FSC activity-node. The PM is defined as follows.

$$
PM = \{\tau_{ij}^{r}\} = \left\{\begin{matrix} \tau_{11}^{r} & \tau_{12}^{r} \dots & \tau_{1J_1}^{r} \\ \tau_{21}^{r} & \tau_{22}^{r} \dots & \tau_{2J_2}^{r} \\ \dots \tau_{N_r1}^{r} & \tau_{N_r2}^{r} & \tau_{N_rJ_{N_r}}^{r} \end{matrix}\right\} \tag{8}
$$

where τ_{ij}^{r} is the pheromone quantity on option node w_{ij}^{r}.

To mimic the pheromone deposition and evaporation, the values of elements in the PM are updated, either through an evaporation process at specific points of time, or through enhancement by ants based on the performances (TP and TLT) of the FSCD produced by each ant. This process of reinforcing and evaporating pheromones over the PM is known as pheromone matrix update and is described in (9):

$$
\tau_{ij}^{r} = \begin{cases} \tau_{ij}^{r} + \Delta\tau_{ij}^{r} + (1-\rho)\tau_{ij}^{r} & if\ option\ w_{ij}^{r}\ is\ selected\ for\ the\ activity\ v_{i}^{r} \\ (1-\rho)\tau_{ij}^{r} & otherwise \end{cases} \tag{9}
$$

ρ in eq.10 is an evaporation factor in the range [0,1]. For the purpose of this study, $\Delta\tau_{ij}^{r}$ is computed as a function of the objectives to be optimized, as expressed in (10).

$$
\Delta\tau_{ij}^{r} = \frac{1}{Q}\left(e^{-\frac{1}{\varepsilon e_{TP,pq}}} + e^{-\frac{e_{TLT,pq}}{\omega}}\right) \forall w_{ij}^{r} \in FSCD_{pq} \tag{10}
$$

where Q is the number of ants in a colony, ε and ω are the weights of the two objectives and $e_{TP,pq}$ and$e_{TLT,pq}$ represent the normalized TP and TLT of the $FSCD_{pq}$, calculated using (1a*) and (1b*).

An important task of every ant while it is on an option node w_{ij}^r is to create its neighbourhood ($N_{w_{ij}^r}$), which is defined as the set of all the possible options the ant can select to correctly perform the i^{th} activity. Formally, we can describe this neighbourhood as follows:

$$N_{w_{ij}^r} = \{w_{ij}^r | w_{ij}^r \in W_i \ ; w_{ij}^r \notin FSCD_{pq};\ w_{ij}^r \ satisfies\ Eqs. 2-6\} \tag{11}$$

Once the ant has created the node's neighbourhood, it selects an option node at each activity node of the FSC through a probabilistic decision rule, which states that the probability that the ant will choose the option w_{ij}^r to perform the primary activity v_i^r is calculated by:

$$P_{w_{ij}^r} = \frac{[\tau_{ij}^r]^\alpha [\eta_{ij}^r]^\beta}{\sum_{w_{ij}^r \in N_{w_{ij}^r}} [\tau_{ij}^r]^\alpha [\eta_{ij}^r]^\beta} \qquad \forall w_{ij}^r \in N_{w_{ij}^r} \tag{12}$$

Here, η_{ij} is a heuristic value computed using (13); α and β are typical ACO parameters with values [0,1] and denote, respectively, the ants' ability to select an option with high pheromone concentration and the ants' ability to select an option with the shortest lead time and lowest cost.

$$\eta_{ij}^r = \frac{\varepsilon}{c_{ij}^r} + \frac{\omega}{t_{ij}^r} \tag{13}$$

If the problem is formulated as a bi-objective one (eq.1), ε and ω are set at 0.5 to apply the above formula. The approach uses P colonies each consisting of Q ants, which tour one after another the nodes of the FSC graph, choosing the appropriate option nodes for each activity-node based on the decision probability rule in (12). For any ant on node i, the choice is made according to this probability rule, based upon both the τ_{ij}^r values (8) and the objectives and constraints of the problem (1)-(6).

To simulate possible FSC disruptions scenarios in raw materials supply, a random value RV_{ijt}^s is associated with each supply option w_{ij}^s at time t. At each iteration, if the random value is less than the supply probability disruption π_{ij}^s of w_{ij}^s, then the maximum production capacity will change randomly as follows:

$$\begin{aligned} CAP_{ijt}^s &= rnd(0:1) \cdot CAPmax_{ij}^s \quad && if\ RV_{ijt}^s < \pi_{ij}^s \\ CAP_{ijt}^s &= CAPmax_{ij}^s && if\ RV_{ijt}^s \geq \pi_{ij}^s \end{aligned} \tag{14}$$

In case $RV_{ijt}^s < \pi_{ij}^s$, the capacity of w_{ij}^s will be restored gradually in the subsequent iterations; more precisely, at time $t+1$, the capacity will be updated according to:

$$CAP_{ijt+1}^s = CAP_{ijt}^s + \left[CAP_{ijt}^s - CAP_{ijt}^s \cdot rnd(0:1)\right] \cdot \frac{1}{t} \tag{15}$$

If the production capacity of the selected option is not sufficient to satisfy the activity demand, the ant will select a further feasible option for that activity, to ensure operations continuity. In such condition, the first selected option would be used with its maximum production capacity, and the new one would satisfy the residual demand. This multiple sourcing policy is adopted also to face market demand fluctuations over the time horizon.

The combination of options resulting when all nodes have been toured by the q^{th} ant of the p^{th} colony represents an FSCD, whose performance in terms of TP and TLT are calculated in (1c) and (1d). The set of FSCDs generated by all ants in the p^{th} colony is then analysed according to normalized performances to identify the best $FSCD_{pq}$, i.e. the $FSCD_{pq*}$ that minimize the objective function in (1). Then, the particular ant $q^*$of the p^{th} colony that has generated the $FSCD_{pq*}$ leaves its pheromone over the graph, triggering the pheromone update process in (10) and (11).

The next colony is then used to tour the network using the PM resulting from the previous colony. All these operations are repeated until the last colony has completed the tour; then, the last generated $FSCD_{pq*}$ will be taken as the final solution of the RFSCD problem. A detailed flowchart of the algorithm is shown in Figure 3, and the proposed algorithm is shown in pseudo-code in the Appendix 1.

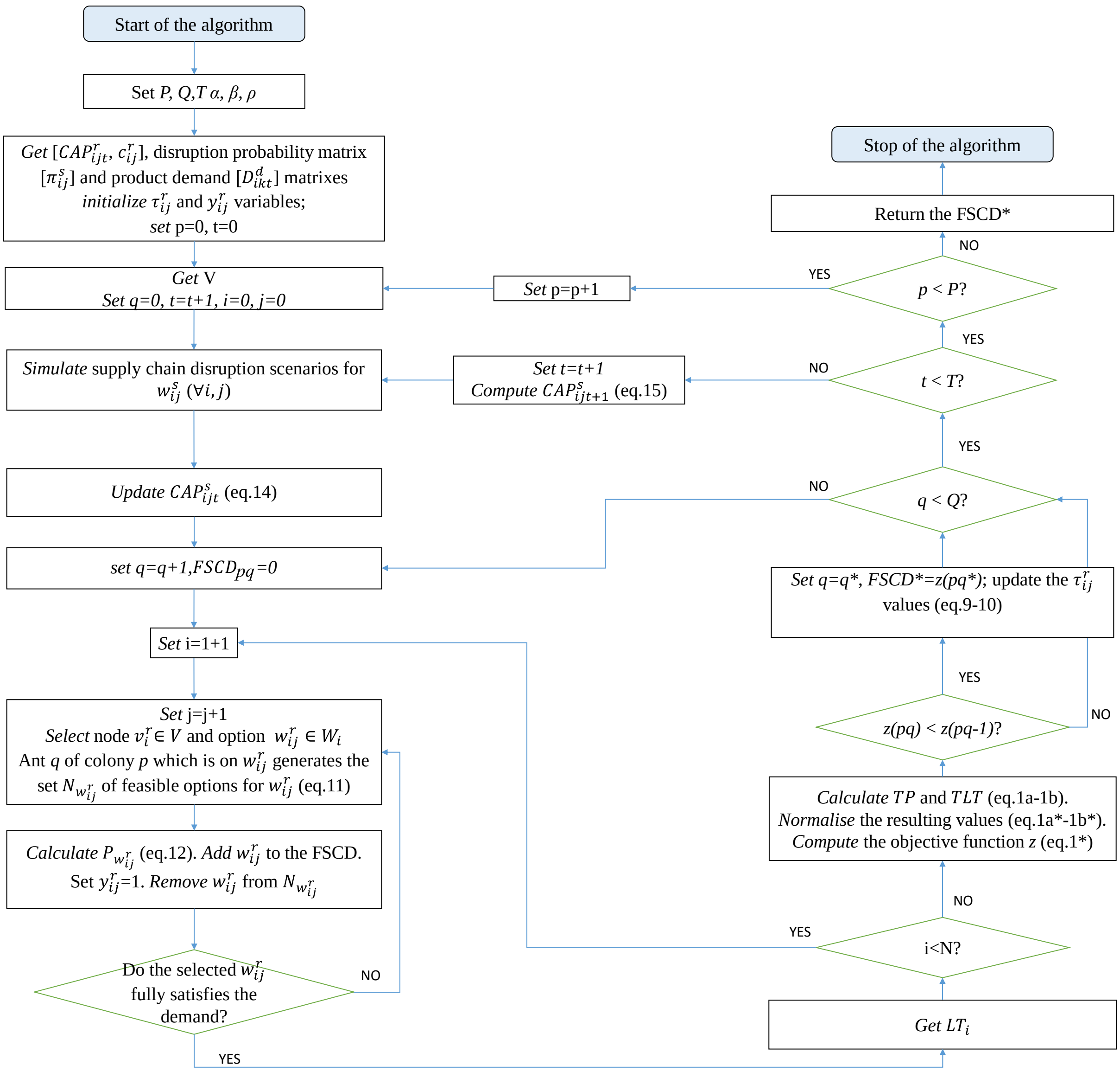

Figure 3: Flowchart of the adapted ACO algorithm to solve the RFSCD problem.

5 Application and experimental results

5.1 Case description and graph representation

A readymade UHT tomato sauce FSC is taken as an example to illustrate and test the adapted ACO algorithm. The considered FSC produces three specific food products: *Tomato & Basil* sauce, *Bolognese* sauce and *Amatriciana* sauce. All the products characteristics and data for solving the RSFSCD problem (e.g. bill of materials, products recipe, HQ price level, LQ price level, etc.) were derived from specific market analyses. These three products are delivered both to the internal market (i.e. the "Italian market" node) and to the international one (i.e. the "international market" node). The related data for solving the problem are shown in Table 4 and were taken from a direct examination of the FSC; the weighted graph representing the FSC network is depicted in Figure 4. Overall, the readymade sauce FSC consists of 16 activities nodes, shared among:

- twelve supplying activity nodes (v_1^s, $v_2^s, \ldots,$ v_{12}^s). The first seven of them must be considered as critical supplying activities, i.e. activities that directly affect the final quality level of the sauces;
- two production activity nodes (v_{13}^p, v_{14}^p);
- two delivering activity nodes (v_{15}^d, v_{16}^d).

The total number of secondary option nodes w_{ij}^r is 53 and their sharing among all the activities is shown in Figure 4. Depending on the product recipe, not all the raw materials might be required; for instance, "meat" is not required for the *Tomato & Basil* sauce and therefore the corresponding node should not be visited when manufacturing this product. For a node to be visited, the demand value at each activity-node depends on the final product demand at the two delivery nodes, which is shown in Table 5 over the time horizon of 12 periods (one year) for each of the three products.

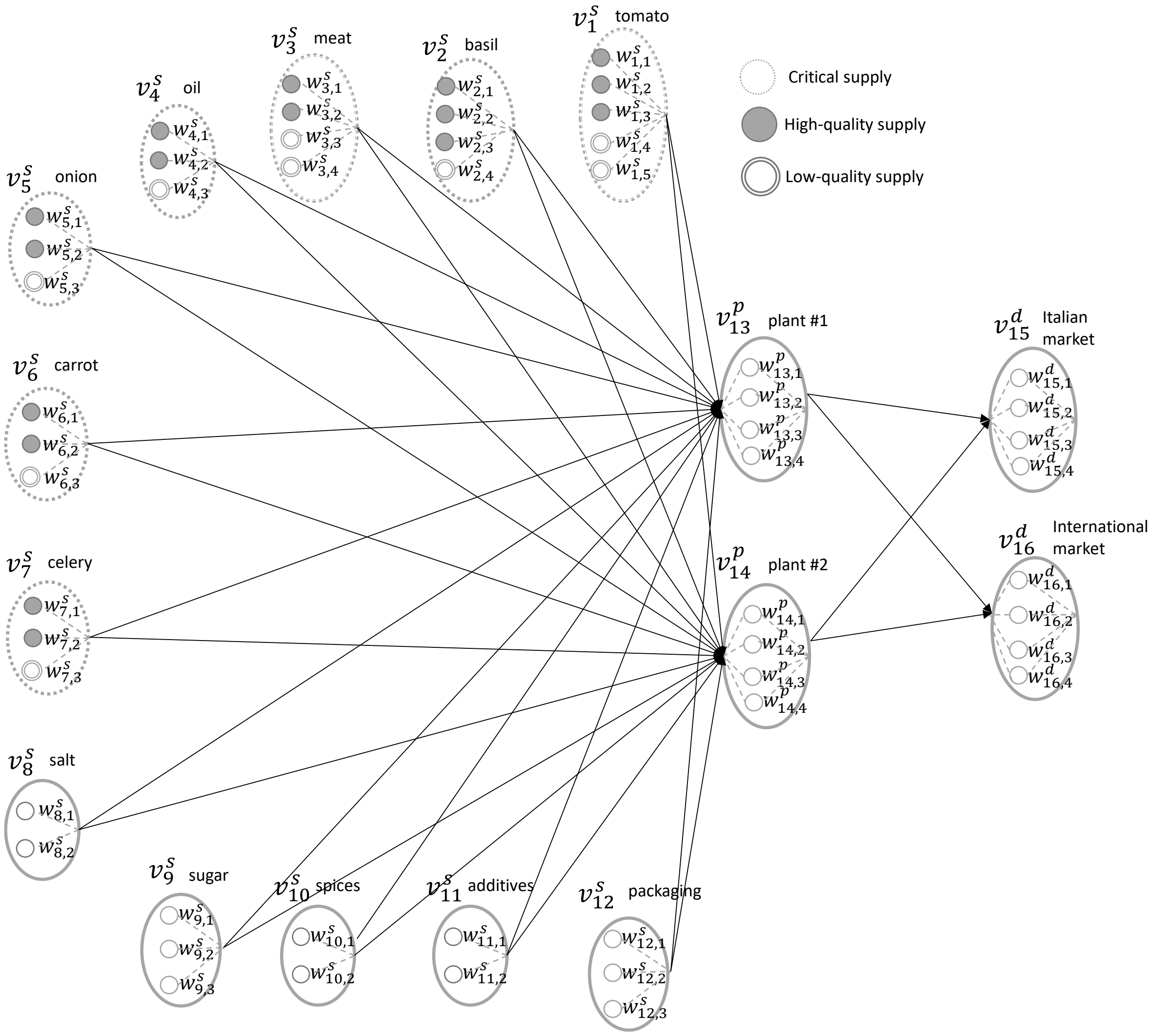

Figure 4: Readymade UHT tomato sauce FSC in graph representation.

Table 4: Input data for the readymade UHT tomato sauce FSC

Activity node - v_i^r	**Option - w_{ij}^r**	**Cost- c_{ij}^r [€/kg]**	**Lead time - t_{ij}^r [days]**	**Capacity - CAP_{ij} [kg]**	**Supply disruption probability - π_{ij}^s [%]**
1 - Tomato (supply - critical)	1*	0.58	5	27410	7
	2*	0.5	4	29480	7
	3*	0.46	6	21610	7
	4**	0.51	9	24860	7
	5**	0.49	8	29846	7
2 - Basil (supply - critical)	1*	0.26	7	1236	7
	2*	0.28	5	1632	7
	3*	0.23	6	1432	7
	4**	0.22	9	1513	7
3 - Meat (supply - critical)	1*	1.25	4	17652	7
	2*	1.21	5	16532	7
	3**	1.20	9	14165	7
	4**	1.21	8	18653	7
4 - Oil (supply - critical)	1*	2.21	5	14240	6
	2*	2.10	4	12650	6
	3**	2.08	8	16520	6
5 - Onion	1*	0.29	4	16310	6

(supply - critical)	2*	0.22	3	13530	6
	3**	0.26	6	17850	6
	4**	0.23	9	12650	6
6 - Carrot (critical supply)	1*	0.21	4	19650	6
	2*	0.20	3	17300	6
	3**	0.19	7	1886	6
7 - Celery (supply - critical)	1*	0.19	5	1071	6
	2*	0.23	4	1015	6
	3**	0.22	8	1081	6
8 - Salt (supply – non-critical)	1	0.10	2	16520	3
	2	0.07	3	17200	3
9 - Sugar (supply – non-critical)	1	0.10	3	14300	3
	2	0.09	4	17650	3
	3	0.06	3	12400	3
10 - Spices (supply – non-critical)	1	0.23	5	60000	3
	2	0.17	3	30000	3
11 - Additives (supply – non-critical)	1	0.18	4	50000	3
	2	0.16	3	40000	3
12 - Packaging (supply – non-critical)	1	0.60	2	245100	3
	2	0.80	4	248200	3
	3	0.40	3	244300	3
13 - Plant 1 (manufacturing)	1	1.52	2	12350	-
	2	1.56	3	14600	-
	3	1.42	5	12030	-
	4	1.36	4	13600	-
14 - Plant 2 (manufacturing)	1	1.58	2	13260	-
	2	1.46	4	11460	-
	3	1.20	3	14520	-
	4	1.31	3	13400	-
15 – Italian market (delivery)	1	1.21	3	13100	-
	2	1.14	5	13500	-
	3	1.19	4	14000	-
16 –International market (delivery)	1	1.37	6	15600	-
	2	1.22	7	18500	-
	3	1.33	5	16200	-
	4	1.41	4	19500	-

(*) HQ critical supplying activity-option (**) LQ critical supplying activity-option

Table 5: Average demand data for the FSC under examination.

	Average monthly demand [kg/month] of UHT tomato sauce – Italian market			Average monthly demand [kg/month] of UHT tomato sauce – international market		
Period	Tomato & basil	Bolognese	Amatriciana	Tomato & basil	Bolognese	Amatriciana
1	10334	12320	10052	15162	15288	15274
2	10370	10355	10330	15200	15370	15390
3	10325	10330	10260	15220	15321	15320
4	10390	10316	10106	15192	15268	15325
5	10380	10329	10234	15213	15310	15302
6	10354	10338	10348	15230	15346	15342
7	10410	10422	10475	15310	15420	15454
8	10460	10473	10492	15395	15490	15467
9	10366	10360	10362	15294	15342	15347
10	10310	10326	10120	15224	15302	15312
11	10250	10302	10154	15187	15248	15280
12	10290	10342	10326	15170	15326	15335

In order to provide the main outcomes of the performance analysis, the FSC is redesigned through the implementation of the proposed algorithm, generating a RFSCD. To evaluate the algorithm effectiveness, the redesign is compared with the current design in terms of performances (TLT and TP). As there are three products in the supply chain, the TP is computed as the sum of the profits generated by each product, while the maximum lead time is taken as the TLT of the system. Moreover, TLT and TP results are averaged across the 12 periods.

The current FSCD is represented in graph in Figure 5. As mentioned earlier, an FSCD is described univocally by a set of ordered subsets of options selected to perform each FSC activity, as defined in (8). In particular, for each subset of option nodes, the first option in the sequence is used to satisfy the activity demand at its maximum production capacity; on the contrary, the last option in the subset will be exploited at a reduced capacity which equals to the residual demand value at that activity node. Therefore, reordering the order of elements (options) in a node would generate a different solution, i.e. a different FSCD. This means that for each node with J_i options, the possible solutions to the problem are ${J_i}^{J_i}$. Overall, the total number of solutions for the proposed FSCD is 1.54E+16.

5.2 Parametrization of the algorithm

5.2.1 Experimental design

The adapted ACO algorithm was coded in Matlab™ and run on an Intel(R) Core™ i3 2.4GHz CPU personal computer, equipped with Microsoft Windows 10 Pro 64-bit operating system. One important aspect in any metaheuristic is to tune the parameters of the algorithm in order to find the best results. There are a number of parameters involved in the ACO algorithm; the most relevant ones are α, β, ρ, τ, P and Q. Also, a relationship exists between P and Q, since fixing one and doubling the other one the execution time doubles (Fidanova & Marinov, 2013).

To set these parameters effectively, several experimental analyses were carried out, considering a range of possible values derived from the literature. In particular, Dorigo et al. (1996) proposed to set the values of α and β from 2 to 5, as well as ρ to 0.5 to get promising results in most ant systems. According to this, and with the aim of representing sufficiently different operating conditions of the algorithm, the following values were tested:

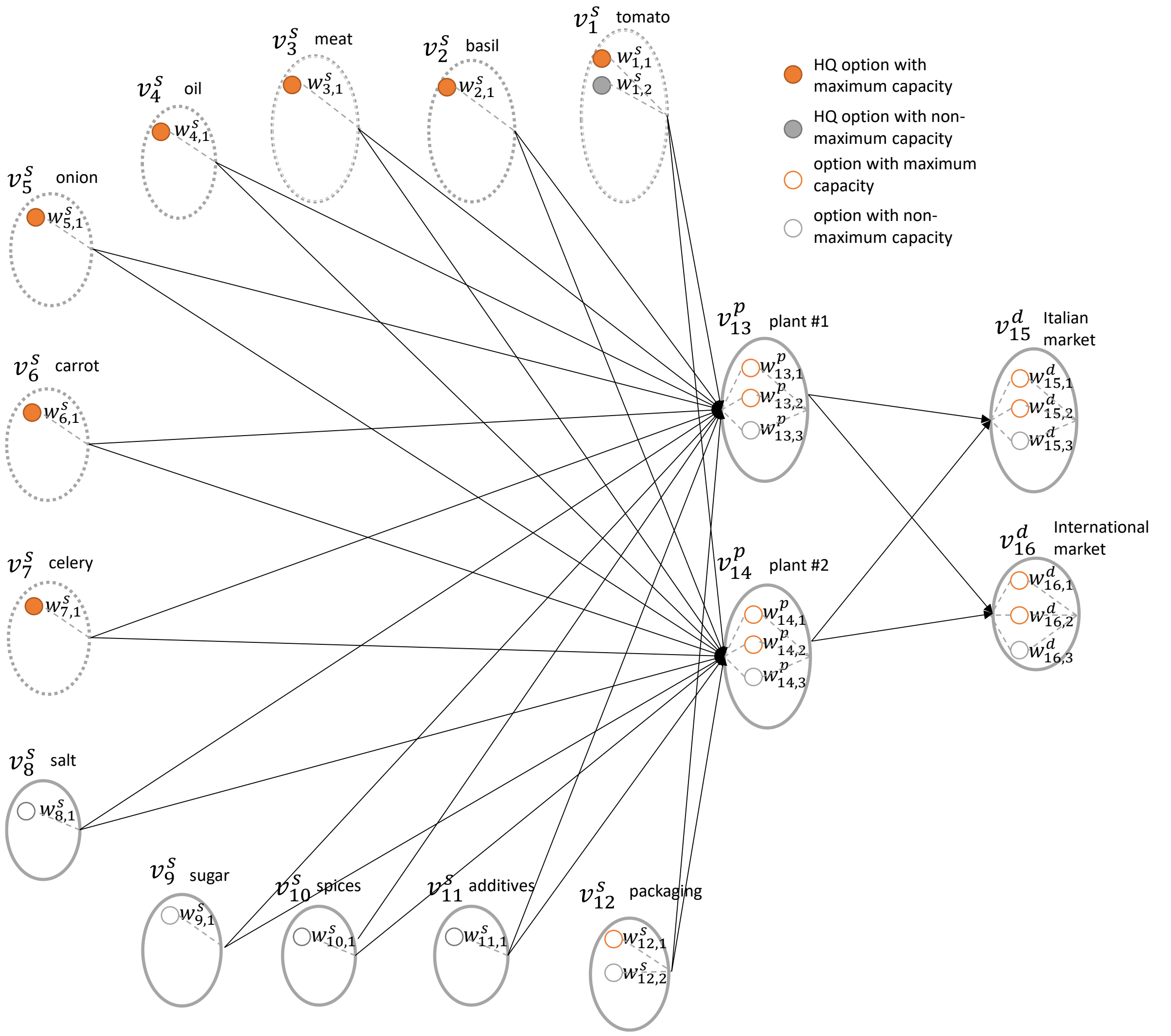

Figure 5: The current readymade UHT tomato sauce FSC design.

- α=1 and β=3, to investigate the condition in which the heuristic value dominates the pheromone concentration in generating RFSCD solutions;
- α=2 and β =2, to investigate the condition in which none of them is dominant;
- α=3 and β=1, instead, to investigate the condition in which pheromone concentration is more important that the heuristic value in generating RFSCD solutions;
- ρ=0.1, ρ=0.5 and ρ =0.9, to reflect three different situations in which the evaporation of the pheromone trail is extremely slow, moderately slow and extremely fast respectively;
- τ=1 and τ=0.5 reflecting the case of high and low initial quantity of pheromone trail;
- P=10 and P=20, with Q=500, in order to intensify only the solution space exploitation phase of the algorithm.

The combination of these settings led to 36 different scenarios. For each scenario, 10 runs of the algorithm were carried out to ensure significance of the outcomes. The results obtained were analysed in terms of performance of the algorithm and of effectiveness of the solution obtained. More precisely, the CPU time required to reach a local optimal solution was evaluated as an indicator of the algorithm computational performance. As far as the solution quality is concerned, this was measured in terms of the total average error rate (e_{tot}), i.e. the mean of the average error rate in the TLT (e_{TLT}) and in the TP (e_{TP}), already defined. To this end, a lower bound of the optimum TLT value (LL_{TLT}) and an upper bound of the optimum TP value (UL_{TP}) were calculated for each period and used in equations (1a) and (1b). These values were obtained by taking only the best option in terms of TP and TLT for all activity nodes.

5.2.2 Analysis of parametrization scenarios

Table 6 shows the average results of the 36 scenarios. For each scenario, a possible solution of the RFSCD problem is provided, together with its performance in terms of e_{TLT} and e_{TP} and of the average CPU time needed to solve the problem. The full analysis of the results returned by the algorithm as a function of the settings used can be found in Appendix 2.

In terms of solution quality, expressed through the error rates, from Table 6 it is easy to see that five different settings of the algorithm return similar results, where the e_{TLT} and e_{TP} are always less than 2%. From the point of view of the system's resilience, this outcome indicates that all these settings are effective in identifying a new supply chain configuration where the TP and TLT are very close to their ideal values. In terms of computational performance, instead, Table 6 also shows that the CPU time differs quite significantly as a function of the parameter setting (from 220 to 460 seconds, approximately), but it always remains in the range of several minutes; therefore, regardless of the setting, the algorithm is sufficiently fast for the analysis of long-term supply chain design problems. In line with this consideration, the most effective settings of the ACO algorithm were determined only in terms of the solution quality. Hence, the following setting turned out to be the most effective: P=20, Q=500, τ=0.5, α=1, β=3, ρ=0.1.

ACO parameters						**RESILIENT FOOD SUPPLY CHAIN DESIGN**																**OBJECTIVES**		**AVERAGE ERROR RATE [%]**			**CPU TIME**
P	Q	α	β	τ	P	v_1^s	v_2^s	v_3^s	v_4^s	v_5^s	v_6^s	v_7^s	v_8^s	v_9^s	v_{10}^s	v_{11}^s	v_{12}^s	v_{13}^p	v_{14}^p	v_{15}^d	v_{16}^d	TLT	TP	e_{TLT}	e_{TP}	e_{TOT}	*sec*
10	500	1	3	0.1	0.5	[3,2]	2	1	2	2	2	2	1	3	2	2	[3,1]	[1,4,2]	[3,2,4]	[2,3,1]	[4,3,1]	53	1466428.515	3.92%	1.59%	2.76%	222.46
10	500	1	3	0.1	0.9	[3,2]	2	1	2	2	2	2	1	3	2	2	[3,1]	[1,4,2]	[3,2,4]	[2,3,1]	[4,3,1]	53	1466428.6	3.92%	1.59%	2.76%	230.22
10	500	1	3	0.5	0.1	[2,1]	2	1	2	2	2	2	1	3	2	2	[3,1]	[1,4,2]	[3,4,1]	[3,2,1]	[3,1,4]	53	1463011.92	3.92%	1.82%	1.89%	222.49
10	500	1	3	0.5	0.5	[2,1]	2	1	2	2	2	1	1	3	2	1	[3,1]	[4,1,2]	[3,4,1]	[2,3,1]	[3,1,4]	52	1463011.92	1.96%	1.82%	1.89%	220.02
10	500	1	3	0.5	0.9	[2,1]	2	1	2	2	2	1	1	3	2	2	[3,1]	[4,3,2]	[4,3,1]	[2,3,1]	[1,3,4]	54	1462925.7	5.88%	1.83%	3.85%	222.58
10	500	2	2	0.1	0.1	[2,1]	2	1	2	2	2	1	1	3	2	2	[3,1]	[1,4,2]	[3,2,4]	[2,3,1]	[4,3,1]	53	1465004.05	3.92%	1.69%	2.80%	253.04
10	500	2	2	0.1	0.5	[1,2,3]	2	1	2	2	2	1	1	3	2	2	[3,1]	[4,1,2]	[3,4,1]	[3,2,1]	[3,2,4]	55	1467082.4	7.84%	1.55%	4.70%	222.83
10	500	2	2	0.1	0.9	[2,1]	2	1	2	2	2	1	1	3	2	2	[3,1]	[4,1,2]	[3,4,1]	[3,2,1]	[3,1,4]	52	1463011.66	1.96%	1.82%	1.89%	222.83
10	500	2	2	0.5	0.1	[3,2]	2	[1,2]	2	2	2	1	1	3	2	1	[3,1]	[4,1,2]	[3,4,1]	[3,2,1]	[1,3,4]	53	1465443.45	3.92%	1.66%	3.79%	222.49
10	500	2	2	0.5	0.5	[3,2]	2	1	2	2	2	1	1	3	2	2	[3,1]	[1,4,2]	[3,4,1]	[2,3,1]	[2,3,1]	55	1468910.28	7.84%	1.43%	4.63%	220.63
10	500	2	2	0.5	0.9	[3,2]	2	1	2	2	2	1	1	3	2	2	[3,1]	[1,4,2]	[3,4,1]	[2,3,1]	[2,3,1]	55	1468629.5	7.84%	1.44%	4.64%	250.01
10	500	3	1	0.1	0.1	[2,1]	3	1	2	[2,1]	2	1	2	3	2	1	[3,1]	[1,4,2]	[3,4,2]	[2,3,1]	[1,3,4]	54	1460669.99	5.88%	1.98%	4.71%	259.55
10	500	3	1	0.1	0.5	[2,1]	2	1	2	2	2	[1,2]	1	3	2	1	[3,1]	[4,1,2]	[3,4,2]	[3,2,1]	[2,1,4]	55	1466501.84	7.84%	1.59%	4.71%	220.46
10	500	3	1	0.1	0.9	[2,1]	2	1	2	2	2	2	1	3	2	2	[3,1]	[1,4,2]	[3,4,1]	[3,2,1]	[3,1,4]	53	1463013.05	3.92%	1.82%	2.87%	236.76
10	500	3	1	0.5	0.1	[2,1]	3	1	2	2	2	2	2	3	2	2	[3,1]	[2,4,1]	[3,4,2]	[3,2,1]	[1,3,4]	56	1467541.21	9.80%	1.52%	5.66%	229.89
10	500	3	1	0.5	0.5	[3,2]	2	2	2	2	2	1	1	3	2	1	[3,1]	[1,4,2]	[3,4,1]	[3,2,1]	[2,3,4]	57	1468968.14	11.76%	1.42%	6.59%	221.76
10	500	3	1	0.5	0.9	[2,1]	2	1	2	2	2	1	1	3	2	2	[3,1]	[2,4,1]	[3,4,2]	[2,3,1]	[3,2,4]	55	1460333.52	7.84%	2.00%	6.76%	254.33
10	500	1	3	0.1	0.1	[2,1]	2	1	2	2	2	1	1	3	2	2	[3,1]	[1,4,2]	[3,2,4]	[2,3,1]	[4,3,1]	53	1466432.51	3.92%	1.59%	2.76%	220.22
20	500	1	3	0.1	0.1	[2,1]	2	1	2	2	2	1	1	3	2	2	[3,1]	[1,4,2]	[3,2,4]	[2,3,1]	[4,3,1]	53	1460663.99	3.92%	1.98%	2.95%	445.04
20	500	1	3	0.1	0.5	[2,1]	2	1	2	2	2	2	1	3	2	2	[3,1]	[1,4,2]	[3,4,1]	[2,3,1]	[1,3,4]	52	1463011.92	1.96%	1.82%	1.89%	445.72
20	500	1	3	0.1	0.9	[2,1]	2	1	2	2	2	2	1	3	2	2	[3,1]	[1,4,2]	[3,4,2]	[2,3,1]	[2,3,4]	54	1464739.28	5.88%	1.71%	3.79%	429.63
20	**500**	**1**	**3**	**0.5**	**0.1**	**[2,1]**	**2**	**1**	**2**	**2**	**2**	**2**	**1**	**3**	**2**	**2**	**[3,1]**	**[1,4,2]**	**[3,4,2]**	**[2,3,1]**	**[1,3,4]**	**52**	**1464268.86**	**1.96%**	**1.74%**	**1.85%**	**443.99**
20	500	1	3	0.5	0.5	[2,1]	2	1	2	2	2	2	1	3	2	2	[3,1]	[1,4,2]	[3,4,1]	[3,2,1]	[3,1,4]	52	1463011.92	1.96%	1.82%	1.89%	442.89
20	500	1	3	0.5	0.9	[2,1]	2	1	2	[2,1]	2	2	1	3	2	1	[3,1]	[4,1,2]	[3,2,1]	[3,2,1]	[1,3,4]	54	1460663.99	5.88%	1.98%	3.93%	445.35
20	500	2	2	0.1	0.1	[3,2]	2	1	2	2	2	1	1	3	2	2	[3,1]	[1,4,2]	[3,4,1]	[2,3,1]	[2,3,1]	55	1468623.03	7.84%	1.44%	4.64%	445.12
20	500	2	2	0.1	0.5	[2,1]	2	[1,2]	2	2	2	1	1	3	2	2	[3,1]	[1,4,2]	[4,3,2]	[3,2,1]	[1,3,4]	54	1464729.98	5.88%	1.71%	3.79%	438.91
20	500	2	2	0.1	0.9	[2,1]	2	1	2	2	2	2	1	3	2	2	[3,1]	[1,4,2]	[3,2,1]	[3,2,1]	[1,3,4]	57	1462220.33	11.76%	1.87%	6.59%	434.02
20	500	2	2	0.1	0.9	[2,1]	2	1	2	2	2	[1,2]	1	3	2	2	[3,1]	[4,2,3]	[4,3,1]	[3,2,1]	[2,3,1]	57	1463222.52	11.76%	1.81%	4.63%	459.25
20	500	2	2	0.5	0.5	[2,1]	3	1	2	2	2	2	2	3	2	2	[3,1]	[2,4,1]	[3,4,2]	[3,2,1]	[1,3,4]	54	1464219.58	5.88%	1.74%	3.81%	435.1
20	500	2	2	0.5	0.9	[3,2]	2	1	2	1	2	1	1	3	2	1	[3,1]	[4,2,3]	[1,3,2]	[3,2,1]	[3,1,4]	57	1464754.65	11.76%	1.70%	6.73%	453.87
20	500	3	1	0.1	0.1	[2,1]	3	1	2	1	2	2	2	3	2	1	[3,1]	[4,2,3]	[3,4,1]	[2,3,1]	[3,1,4]	55	1466519.22	7.84%	1.59%	3.81%	445.35
20	500	3	1	0.1	0.5	[2,1]	3	1	2	2	2	2	2	3	2	2	[3,1]	[2,4,1]	[3,4,2]	[3,2,1]	[1,3,4]	55	1467196.8	7.84%	1.54%	4.69%	454.55
20	500	3	1	0.1	0.9	[2,1]	3	1	2	2	2	2	2	3	2	2	[3,1]	[2,4,1]	[3,4,2]	[3,2,1]	[1,3,4]	55	1467934.78	7.84%	1.49%	4.67%	447.23
20	500	3	1	0.5	0.1	[2,1]	2	1	2	2	2	2	1	3	2	2	[3,1]	[1,4,2]	[3,4,2]	[2,3,1]	[2,3,4]	54	1467891.02	5.88%	1.49%	4.69%	422.55
20	500	3	1	0.5	0.5	[3,2]	2	1	2	1	2	1	1	3	2	1	[3,1]	[4,2,3]	[1,3,2]	[3,2,1]	[3,1,4]	57	1463909.27	11.76%	1.76%	6.76%	459.25
20	500	3	1	0.5	0.9	[2,1]	2	1	2	2	2	1	1	3	2	2	[3,1]	[4,3,2]	[4,3,2]	[2,3,1]	[2,1,4]	52	1461235.22	1.96%	1.94%	2.76%	443.99

Table 6: Results for the resilient FSC designs (each averaged over 10 runs).

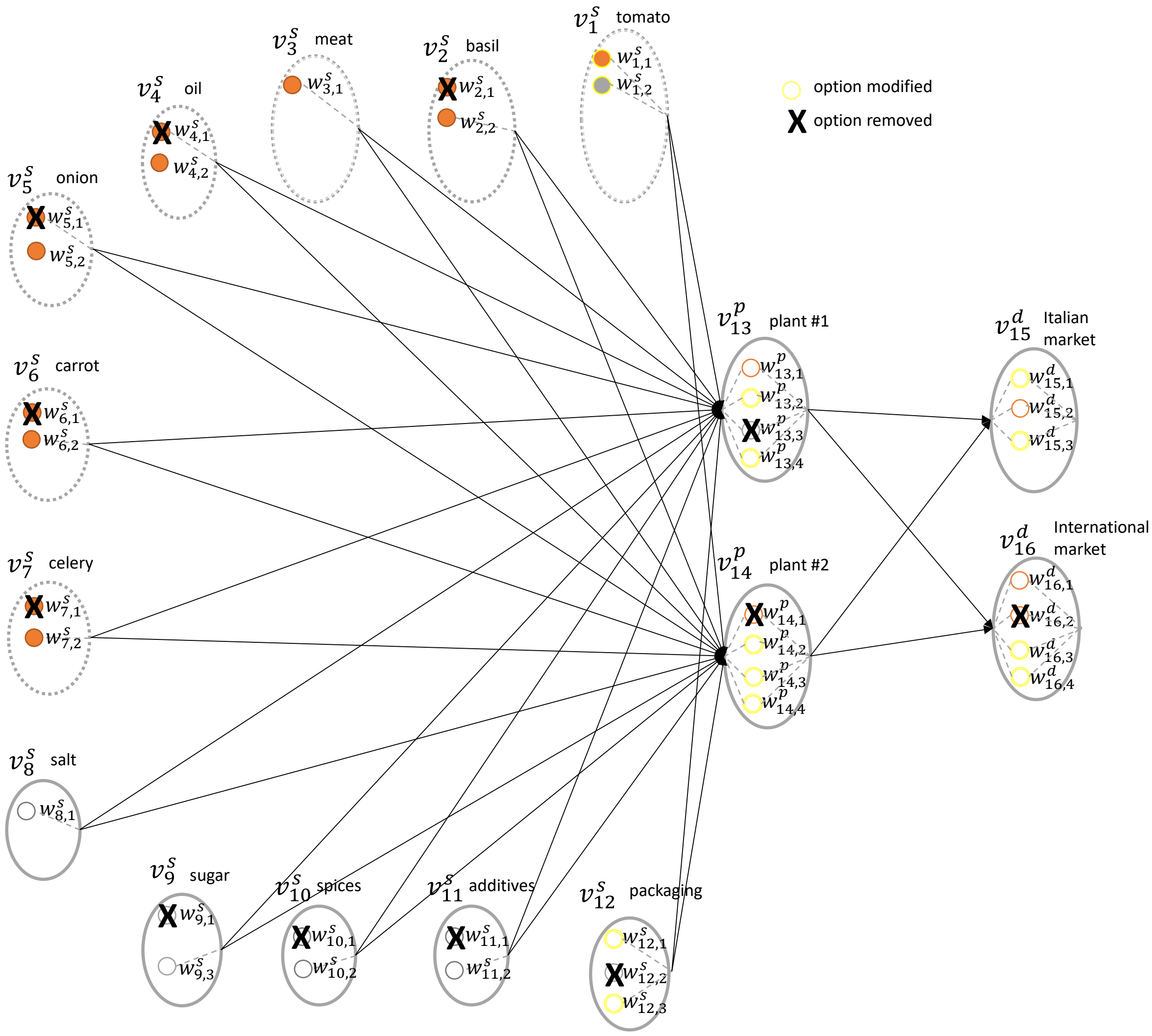

Figure 6: The readymade UHT tomato sauce RFSCD generated by the ACO algorithm.

5.3 Supply chain redesign and sensitivity analysis

In order to illustrate the use of the adapted ACO algorithm, this paper aims to redesign the tested FSC through the implementation of the proposed algorithm, generating an RFSCD. To evaluate the result, the redesign is compared with the current design in terms of performances (TLT and TP). The current FSCD is represented by the graph in Figure 5. The new FSC generated by the algorithm is illustrated in Figure 6. The comparison of Figure 5 and Figure 6 highlights that the proposed ACO algorithm has removed parts of the original FSCD and introduced new ones. These changes aim at ensuring that every subset of selected options is able to fully satisfy the activity demands at each time period in presence of uncertainties, as well as to globally maintain business operations continuity in all the considered disruption scenarios of raw materials supply, making the entire FSC more resilient. For instance, the following changes can be seen:

- v_1^s “tomato” (critical node): the same options are selected for this node, i.e. $w_{1,1}^s$ and $w_{1,2}^s$. However, in the RFSC $w_{1,2}^s$ must be inserted at maximum capacity and $w_{1,1}^s$ at reduced capacity equal to the residual demand at the node;
- v_{12}^s “packaging” (non-critical node): $w_{12,2}^s$ is eliminated while $w_{12,3}^s$ must be inserted at its maximum capacity and$w_{12,1}^s$ at reduced capacity equal to the residual demand at the node;
- v_{13}^p “plant 1”: $w_{13,3}^p$ is eliminated and $w_{13,1}^p$ is set at its maximum capacity. In addition, a new option $w_{13,4}^p$ is introduced as set at its maximum capacity. In option $w_{13,2}^p$ instead, the quantity required has been reduced to the residual demand seen by the node;
- v_{15}^d “Italian market”: all options are kept, but reallocating the total demand at each option. In particular, $w_{15,2}^d$ and $w_{15,3}^d$ are set at their maximum capacity, while the residual capacity is attributed to the $w_{15,1}^d$ option;
- v_{16}^d “international market”: $w_{16,2}^d$ is eliminated, while $w_{16,1}^d$ is kept at its same capacity and $w_{16,3}^d$ kept at maximum capacity. In additions, a new option $w_{16,4}^d$ is introduced and set at reduced capacity, equal to the residual demand faced by the node.

Table 7 contains a comprehensive list of all changes that were introduced by the algorithm.

Table 7: results provided by the algorithm.

Activity	v_i^r	**FSCD vs. RFSCD (after ACO implementation)**
Tomato (critical supply)	v_1^s	• $w_{1,2}^s$ set at maximum capacity • $w_{1,1}^s$ set at reduced capacity (residual demand faced by the node)
Basil (critical supply)	v_2^s	• $w_{2,1}^s$ eliminated • $w_{2,2}^s$ set at maximum capacity
Meat (critical supply)	v_3^s	same configuration
Oil (critical supply)	v_4^s	• $w_{4,1}^s$ eliminated • $w_{4,2}^s$ set at maximum capacity
Onion (critical supply)	v_5^s	• $w_{5,1}^s$ eliminated • $w_{5,2}^s$ set at maximum capacity
Carrot (critical supply)	v_6^s	• $w_{6,1}^s$ eliminated • $w_{6,2}^s$ set at maximum capacity
Celery (critical supply)	v_7^s	• $w_{7,1}^s$ eliminated • $w_{7,2}^s$ set at maximum capacity
Salt (non-critical supply)	v_8^s	same configuration
Sugar (non-critical supply)	v_9^s	• $w_{9,1}^s$ eliminated • $w_{9,3}^s$ set at maximum capacity
Spices (non-critical supply)	v_{10}^s	• $w_{10,1}^s$ eliminated • $w_{10,2}^s$ set at maximum capacity
Additives (non-critical supply)	v_{11}^s	• $w_{11,1}^s$ eliminated • $w_{11,2}^s$ set at maximum capacity

Packaging (non-critical supply)	v_{12}^{s}	• $w_{12,2}^{s}$ eliminated • $w_{12,3}^{s}$ set at maximum capacity • $w_{12,1}^{s}$ set at reduced capacity (residual demand faced by the node)
Plant 1 (manufacturing)	v_{13}^{p}	• $w_{13,3}^{p}$ eliminated • $w_{13,1}^{p}$ set at maximum capacity • $w_{13,2}^{p}$ set at a reduced quantity (residual demand faced by the node) • new option $w_{13,4}^{p}$ introduced and set at maximum capacity
Plant 2 (manufacturing)	v_{14}^{p}	• $w_{14,1}^{p}$ eliminated • capacity modified for $w_{14,3}^{p}$ and $w_{14,2}^{p}$ • new option $w_{14,4}^{p}$ introduced and set at maximum capacity
Italy (market)	v_{15}^{d}	• $w_{15,2}^{d}$ and $w_{15,3}^{d}$ set at maximum capacity • $w_{15,1}^{d}$ set at the residual capacity
Abroad (market)	v_{16}^{d}	• $w_{16,2}^{d}$ eliminated • $w_{16,1}^{d}$ kept at the same capacity • $w_{16,3}^{d}$ kept at minimum capacity • new option $w_{16,4}^{d}$ introduced and set at reduced capacity (residual demand faced by the node)

The comparison between the two FSC configurations in terms of the key performance parameters is shown in Figure 7. It can be concluded that the implementation of the proposed ACO algorithm to the case study reduced the TLT by approximately 18.75% and increased the TP by 1.74% simultaneously, compared to the original configuration. Therefore, the new design enhances both the resilience and the efficiency of the entire FSC (compared to the current situation).

The proposed ACO was further tested by means of a sensitivity analysis, to evaluate the changes in the outputs generated by a modification of the weights of the objective functions, i.e. ε and ω. The previous experimental studies were carried out by setting both weights at 0.5, reflecting the situation where the decision maker considers the two objectives equally important. The best setting of the ACO parameters, previously found, is assumed.

The sensitivity analysis was carried out considering two further situations, specifically:

- ε=0.2 and ω=0.8, i.e. the case in which TLT is more important than TP in the decision-making process; and
- ε=0.8 and ω=0.2, i.e. the (opposite) situation in which TP is more important than TLT in the decision-making process.

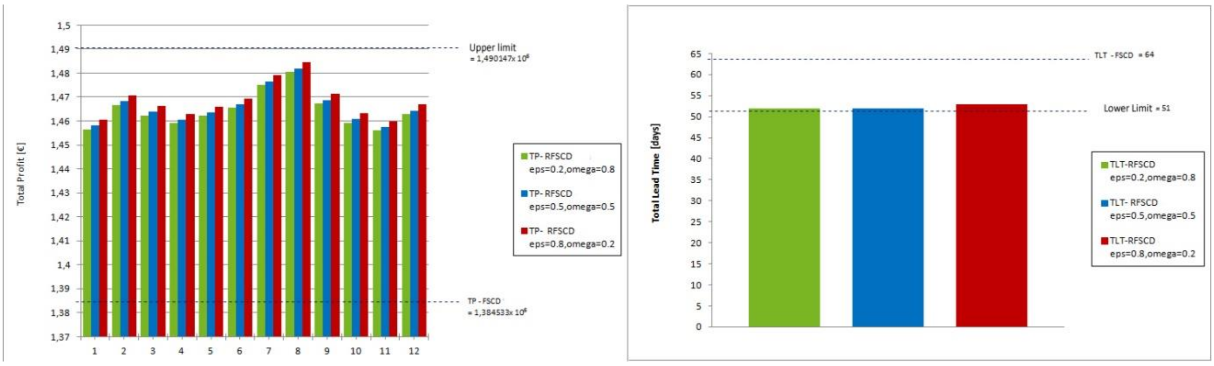

Figure 7: The objectives values of the generated RFSCDs by varying ε and ω.

Considering the same sources of uncertainty (i.e. disruptions in raw materials supply and food market demand fluctuations), the algorithm generated different resilient designs for the FSC considered, as a function of the weights set for the objectives functions. The resulting RFSCDs are detailed in Table 7, while the values of the objective functions at each period are shown in Figure 7. It can be concluded that the adapted ACO algorithm is able to generate different solutions for the RFSCD problem and that such solutions are perfectly consistent with the different optimization purposes.

Table 7: The generated RFSCDs by changing $\boldsymbol{\varepsilon}$ and $\boldsymbol{\omega}$ values.

Weighting factors		Resilient Food Supply Chain Design															
ε	ω	v_1^s	v_2^s	v_3^s	v_4^s	v_5^s	v_6^s	v_7^s	v_8^s	v_9^s	v_{10}^s	v_{11}^s	v_{12}^s	v_{13}^p	v_{14}^p	v_{15}^d	v_{16}^d
0.2	0.8	[2,1]	2	1	2	2	2	2	1	3	2	2	[3,1]	[1,4,2]	[4,3,1]	[1,2,3]	[3,1,4]
0.5	0.5	[2,1]	2	1	2	2	2	2	1	3	2	2	[3,1]	[1,4,2]	[3,4,2]	[2,3,1]	[1,3,4]
0.8	0.2	[3,2]	2	1	2	2	2	2	1	3	2	2	[3,1]	[4,1,2]	[3,4,2]	[2,3,1]	[3,1,4]

5.4 Comparison with alternative approaches

To confirm the effectiveness of the ACO algorithm, the same FSCD problem was solved using two additional approaches and the related results were compared to those returned by the proposed algorithm.

5.4.1 Multi-objective optimization

The first approach consists in modelling the problem as a bi-objective one (maximum TP and minimum TLT) and solving it with a multi-objective optimization software. To this end, the set of equations 1-6 previously described in section 4.2 was embodied in a Microsoft Excel™ model with VBA macros, together with the input data provided in section 5.1. Macros were used to generate random values of the disruption probabilities (10 values per period) as well as to switch among the different periods. ModeFRONTIER release 2018R3 (ESTECO S.p.A.) for Windows was used in support to the Microsoft Excel™ model to create the workflow of the design problem and to solve it with multi-objective optimization (Figure 8). The problem formulation in ModeFRONTIER requires 53 decision variables per product (159 variables overall), which were grouped into three input vectors because of their similarities across the three products. Decision variables reflect the y_{ij}^{r} values in eq.6. NSGA-II (Deb et al., 2002) was selected as the multi-objective evolutionary algorithms to solve the problem because of its effectiveness. The multi-objective optimization algorithm returns approximately 1,500 configurations for each period evaluated and for each value of the disruption probability ($\approx 1.8*10^5$ results). Running the Microsoft Excel™ macros to generate the disruption probabilities and the ModeFRONTIER model for multi-objective optimization on an Intel® Core™ i7 laptop with 32 GB RAM required approximately 3-4 minutes per period (35-45 minutes overall). The outcomes were then exported and subsequently elaborated in Microsoft Excel™ to evaluate their feasibility with respects to the problem constraints and to assign the relative importance to the two objective functions, so as to identify the most suitable solutions.

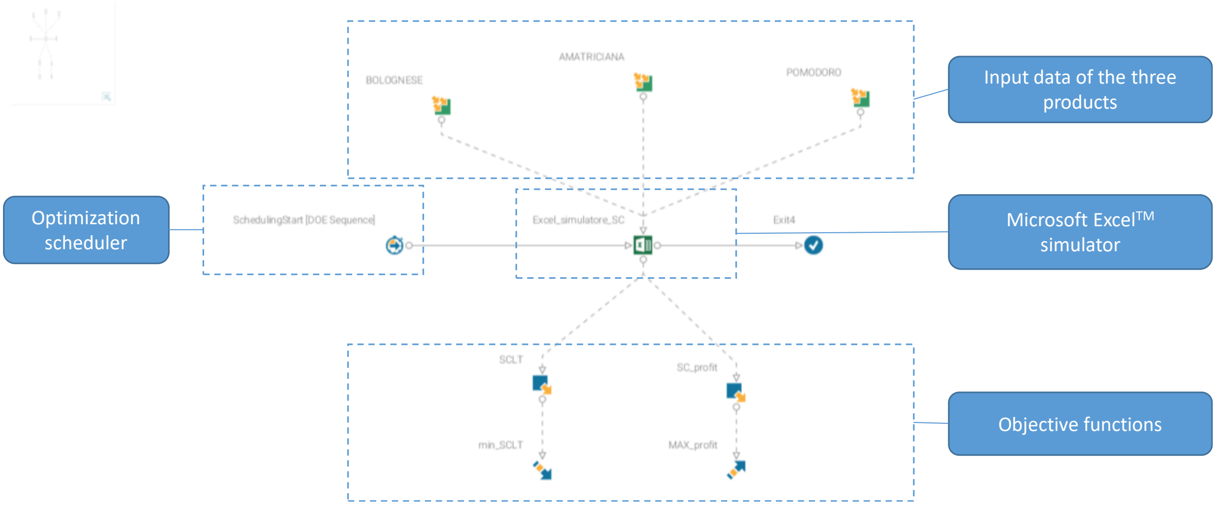

Figure 8: multi-objective optimization workflow in ModeFRONTIER.

The top-30 results returned by the multi-objective optimization software are shown in Table 8. From this table (which is limited to the minimum TLT identified in the optimization) it is easy to see that TP does not exhibit a wide variability; rather, it oscillates around two possible values. This characteristic is due to the constraint set about the market demand, which must always be satisfied (cf. section 4.2); because of this constraint, the turnover generated by supply chain cannot vary to an appreciable extent. More precisely, its maximum value is obtained when the demand can be satisfied using high quality supplies, while its minimum value is obtained if the demand cannot be satisfied using high quality supplies only and therefore the final product is sold at the low quality price. Oscillations around the maximum or minimum value can be due, for instance, to the different option nodes activated, which involve different production costs. Consequently, TP computed as the difference between turnover and cost, does not show a wide variability, as can also be appreciated looking at the previous results in Table 6. Nonetheless, it is interesting to note that the results Table 8 are in line with those proposed previously in Table 6, both in terms of TLT and TP. Indeed, the minimum TLT returned by the multi-objective optimization scores 52 days, and the best TP is around 1,475,000 €; this latter is slightly higher than that returned by the ACO model, which could be attributed to the random disruption probability values generated.

TLT [days]	TP [€]
52	1474944.62
52	1474848.73
52	1465509.04
52	1465501.37
52	1465486.02
52	1465139.54
52	1465129.31
52	1464669.04
52	1464642.19
52	1464626.85
52	1464620.46
52	1464601.28
52	1464314.89
52	1464284.20
52	1464273.97
52	1464268.86
52	1464243.29
52	1455702.68
52	1455344.69
52	1455273.10
52	1454503.42
52	1454440.77
52	1454421.59
52	1454413.92
52	1454392.19
52	1454168.44
52	1454164.61
52	1454160.77
52	1454139.04
52	1454053.37

Table 8: top-30 configurations returned by the multi-objective optimization.

5.4.2 Mathematical programming solver

The second approach was to model the single-objective problem (eq.1* with ε=ω=0.5) in IBM ILOG CPLEX Optimization Studio, a solver for both mathematical programming and constraint programming problems. According to the problem structure, the model developed in IBM ILOG CPLEX consists again in 53 binary decision variables per product (159 variables overall), reflecting the option nodes in the network. For each option node, further data to be included in the model are capacity, lead time, disruption probability and production cost. Moreover, each option node can be high-quality or low-quality. The main characteristics of the final products include their selling price (high-quality or low-quality) and the market demand (national and international). These latter values are specific for each period; therefore, each period was modelled separately in IBM ILOG CPLEX. Again, the disruption probabilities were generated using Microsoft Excel™ (10 values per period). Overall, 120 different sets of data (12 periods x 10 disruption probabilities) were imported in IBM ILOG CPLEX, which means that 120 problems were solved separately. The set of solutions is too long to be fully reported in this paper; as an example of the solution provided, Table 9 shows the solution returned by IBM ILOG CPLEX for period 1 with a given set of disruption probabilities. As Table 9 shows, the solution is, once again, similar to that returned by the proposed ACO algorithm. In general, the solver privileges the activation of the first option node available, thus generating a TLT slightly higher than that returned by the proposed approach, but also a very good TP. Details about the option nodes activated are provided in Table 10.

RESILIENT FOOD SUPPLY CHAIN DESIGN																**OBJECTIVES**		**AVERAGE ERROR RATE [%]**		
v_1^s	v_2^s	v_3^s	v_4^s	v_5^s	v_6^s	v_7^s	v_8^s	v_9^s	v_{10}^s	v_{11}^s	v_{12}^s	v_{13}^p	v_{14}^p	v_{15}^d	v_{16}^d	$\boldsymbol{TLT}$	$\boldsymbol{TP}$	$\boldsymbol{e_{TLT}}$	$\boldsymbol{e_{TP}}$	$\boldsymbol{e_{TOT}}$
[1,2]	1	1	1	1	1	1	1	1	1	2	1	[1,2,3]	[1,2,3]	[1,2,3]	[1,2,3]	57	1,482,433.12	3.92%	0.52%	2.20%

Table 9: example of solution generated by IBM ILOG CPLEX for period 1.

Activity	v_i^r	**Option nodes activated**
Tomato (critical supply)	v_1^s	• $w_{1,1}^s$ set at maximum capacity • $w_{1,2}^s$ set at reduced capacity (equal to the residual demand at the node)
Basil (critical supply)	v_2^s	• $w_{2,1}^s$ set at maximum capacity
Meat (critical supply)	v_3^s	• $w_{3,1}^s$ set at maximum capacity
Oil (critical supply)	v_4^s	• $w_{4,1}^s$ set at maximum capacity
Onion (critical supply)	v_5^s	• $w_{5,1}^s$ set at maximum capacity
Carrot (critical supply)	v_6^s	• $w_{6,1}^s$ set at maximum capacity
Celery (critical supply)	v_7^s	• $w_{7,1}^s$ set at maximum capacity
Salt (non-critical supply)	v_8^s	• $w_{8,1}^s$ set at maximum capacity
Sugar (non-critical supply)	v_9^s	• $w_{9,1}^s$ set at maximum capacity
Spices (non-critical supply)	v_{10}^s	• $w_{10,1}^s$ set at maximum capacity
Additives (non-critical supply)	v_{11}^s	• $w_{11,1}^s$ eliminated • $w_{11,2}^s$ set at maximum capacity
Packaging (non-critical supply)	v_{12}^s	• $w_{12,1}^s$ set at maximum capacity
Plant 1 (manufacturing)	v_{13}^p	• $w_{13,1}^p$ set at maximum capacity • $w_{13,2}^p$ set at maximum capacity • $w_{13,3}^p$ set at reduced capacity
Plant 2 (manufacturing)	v_{14}^p	• $w_{14,1}^p$ set at reduced capacity • $w_{14,3}^p$ set at maximum capacity

		• $w_{14,2}^{p}$ set at reduced capacity
Italy (market)	v_{15}^{d}	• $w_{15,2}^{d}$ and $w_{15,3}^{d}$ set at reduced capacity • $w_{15,1}^{d}$ set at maximum capacity
Abroad (market)	v_{16}^{d}	• $w_{16,1}^{d}$ set at maximum capacity • $w_{16,2}^{d}$ set at maximum capacity • $w_{16,3}^{d}$ set at reduced capacity.

Table 10: example of solution generated by IBM ILOG CPLEX for period 1 - details.

6 Conclusions

Supply chain disruption risks and uncertainties are growing in number and modern food supply chains are among the most vulnerable to such risks. This study has proposed a new approach to design a multi-product food supply chain that is both efficient in terms of performance (i.e. costs and responsiveness) as well as resilient to disruptions in raw material supply and demand variability.

The proposed approach begins with a preliminary analysis of the main characteristics of the specific food supply chain to be analysed, based on a graph theory representation of the chain. Then, a bi-objective resilient food supply chain design (RFSCD) problem is formulated as a non-linear optimization problem, with two objectives (total profit and total lead time). Subsequently, a metaheuristic algorithm based on the ant colony optimization is used to solve the RFSCD problem. This type of algorithm was chosen because the resilient supply chain characteristics of self-adaptation and self-coordination can be well captured by the self-organization features of ant colonies.

The proposed algorithm was tested on a case study of a real readymade UHT tomato sauce chain. The algorithm parameters were studied to determine the best settings, and the tests made show that the proposed approach is effective in generating RFSCDs very close to the optimal solution (if available) of the problem in a relatively short time.

Finally, a sensitivity analysis of the case study results was carried to test the effectiveness of the algorithm as a function of the weights defined for the two objective functions. Results of such analysis allows concluding that the algorithm is able to generate outcomes that are consistent with the optimization purpose, and that the proposed algorithm is expected to be useful to help managers plan a resilient design of their supply chain.

Future works can investigate the adaptation of the proposed algorithm to RFSCD problems in different contexts, thus taking into account further possible disruptions and risks.

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Appendix 1: Pseudo-code of the ACO algorithm adapted to solve RFSC configuration problem

```
begin
    set Q and P;
    set the graph G={V,A} which models the RFSC configuration problem;
    for t=1 to T do
        get the set of nodes V and sub-nodes;
        get the weights at each sub-node;
        do supply disruption simulation;
        for p=1 to P do
            for q=1 to Q do
                set an empty solution FSCD_pq= [ ];
                while V≠{} do
                    select any supply task v_i^r∈V;
                    set the neighborhood N_{v_ij^r};
                    while demand at v_i^r is not satisfied do
                        computeP_{v_ij^r}  ∀ v_ij^r ∈ N_{v_ij^r};
                        select a v_ij^r based on the probability decision rule;
                        add the selected option to the solution, FSCD_pq←v_ij^r;
                        delete v_ij^r from N_{v_ij^r}
                    end
                    delete v_i^r from V;
                end
                set the LT_i∀ v_i^r ∈FSCD_pq;
                compute TP_pq ;
                compute TLT_pq;
            end
            define the best FSCD_pq*;
            forall v_ij^r ∈FSCD_pq* do
                modify PM;
                increase and evaporate pheromones (pheromone matrix update);
            end
        end
    end
    return the FSCD_pq* as the optimal RFSC design;
end
```

Appendix 2: detailed analyses of the objective function values

To further illustrate the behaviour of our algorithm, Figure A-1(a) shows the objective function values z and the two objective values separately for each ant of all colonies, as they were obtained changing α and β values and setting P=10, τ =1 and ρ=0.5. As reported in Figure A-1(a), although the algorithm converges with any setting, the local minima reached are different. More precisely:

- for α=3 and β=1 (green line in Figure 6), the algorithm converges to the worst local minimum solution but faster than the other two setting of parameters;
- for α=2 and β=2 (red line in Figure 6), the algorithm converges to a better solution than the previous one and shows similar rate of convergence;
- for α=1 and β=3 (blue line in Figure 6), the algorithm converges to the best local minimum solution, but with the lowest convergence.

For the sake of clarity, a more detailed representation of the same runs is reported in Figure A-1(b), which shows the values of the two objectives for each "best" ant of all colonies (i.e. the ant that has generated the best $FSCD_{pq*}$ for each colony). Figure A-1(b) shows clearly that both the convergence time of the algorithm and the performance of the generated solutions are the lowest for α=3 and β=1, intermediate for α=2 and β=2, and the biggest for α=1 and β=3.

Consequently, these analyses confirm that the setting that provides the most effective results is α=1 and β=3. Similar analyses on the remaining parameter settings have shown that the algorithm is able to converge to even better solutions if initialising the values of the PM to τ=0.5, regardless of the remaining parameters. According to this result, both reinforcing the exploitation phase (i.e. doubling the number P of colonies) and using the best value for τ (0.5) are required to define the best values for $\alpha$and β. Therefore, Figure A-2(a-b) illustrate the objective function z values and the two objectives (TP and TLT) values that are reported for each ant and for each best ant of all colonies respectively, changing α and β values and setting P=20,τ =0.5 and ρ=0.5. Figure A-2(a-b) shows that for α=2, β=2 and for α=3, β=1 (depicted in red and green, respectively) the algorithm converges quickly to solutions with bad performances in terms of objectives of the problems. Concluding, we can again see that the best setting of α and β parameters is α=1 and β=3 (in blue in Figure A-2), since it allows the algorithm to reach the best local minimum.

Finally, several analyses were carried out to tune last parameter ρ, by fixing the remaining parameters to the best found values (P=20, τ=0.5, ρ=0.5, α=1 and β=3). ρwas set at 0.1, 0.5 and 0.9 (Dorigo, Dorigo, & Colorni, 1996). In Figure A-3(a-b) the objective functions are reported for each ant and each best ant respectively and we can conclude that the best results for our problem are found by setting ρ =0.1.

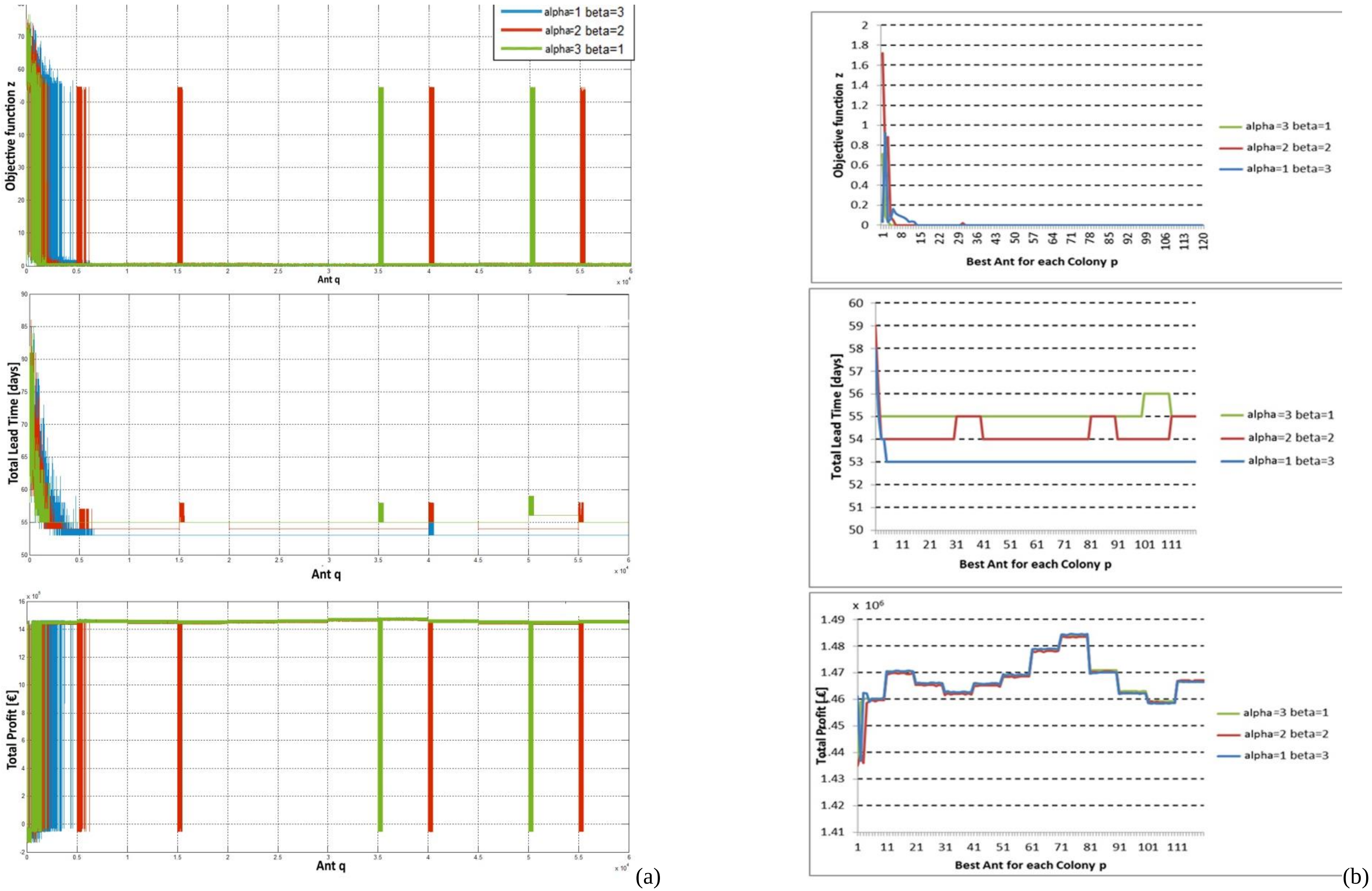


Figure A-1: objective function and objective values for each ant (a) and best ant (b) with P=10, τ=1, ρ=0.5 and varying α and β.

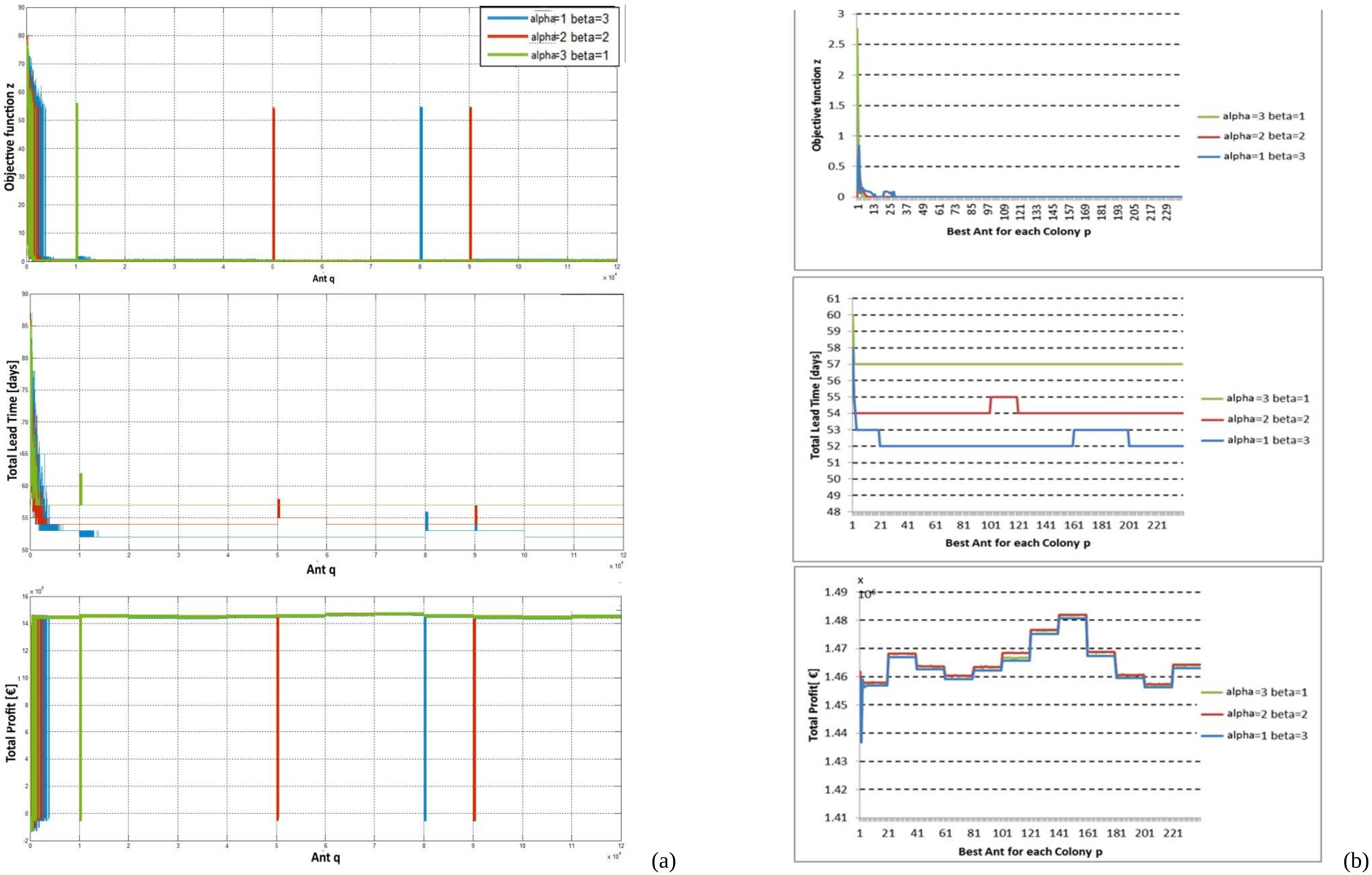
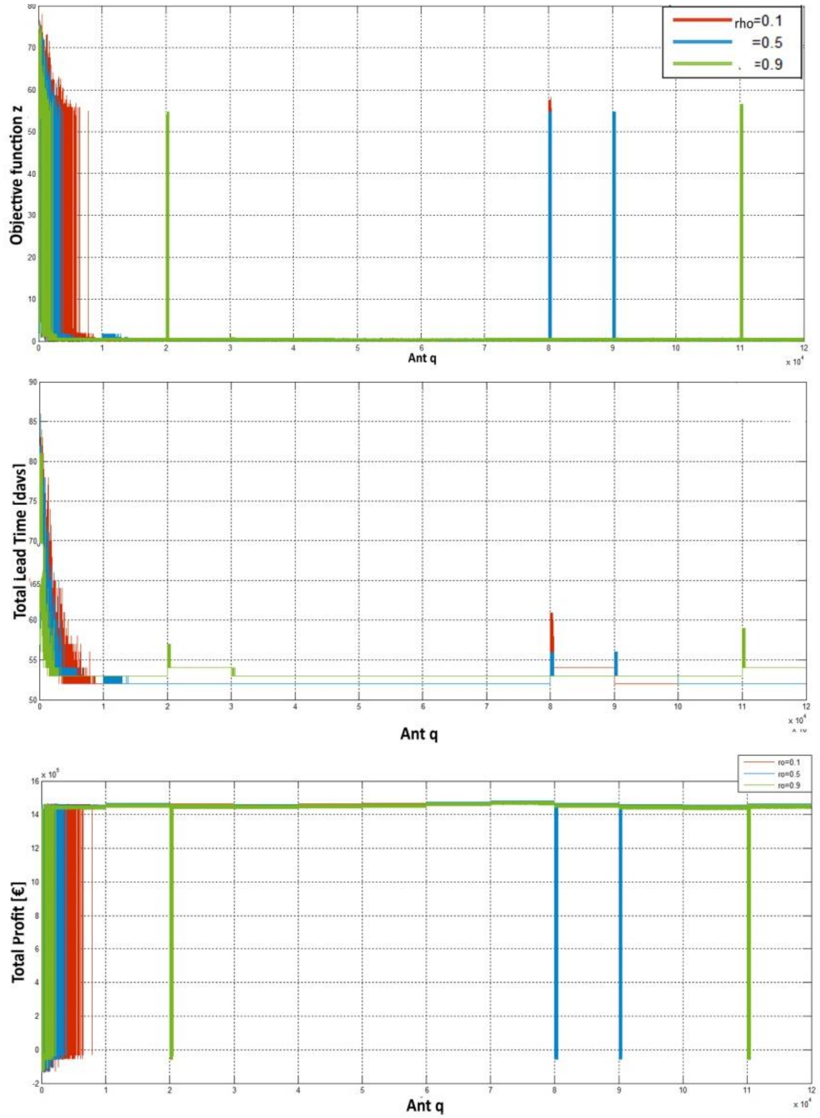
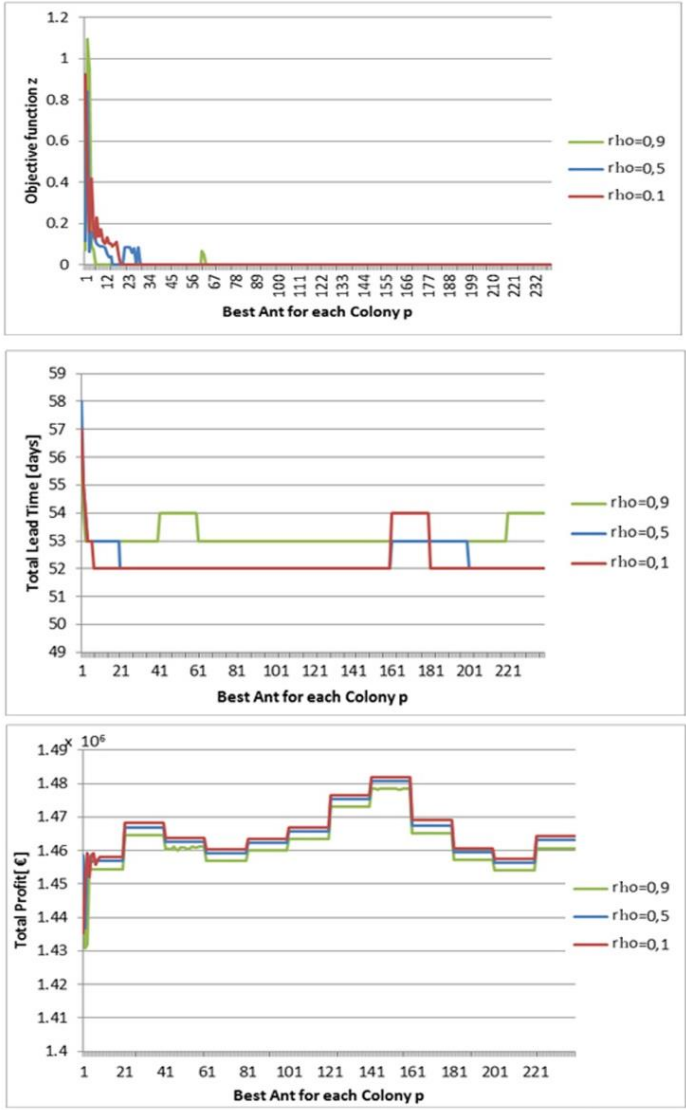


Figure A-2: objective function and objective values for each ant (a) and best ant (b) with P=20, τ=0.5, ρ=0.5 and varying α and β.



(a)



(b)

Figure A-3: objective function and objective values for each ant (a) and best ant (b) with P=20, τ=0.5, α=1, β=3 and varying ρ.