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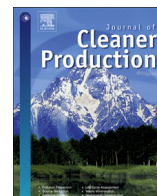
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The Honeycomb model: A platform for systematic analysis of different manufacturing scenarios for fast-moving consumer goods

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ABSTRACT

Consumer interest in environmentally friendly goods has introduced concepts and ideas about the manufacturing/consumption of local products as an alternative to large-scale centralized manufacturing. It has been proposed that small-scale production will reduce the CO₂ emissions associated with transportation and strengthen local economies at the same time. However, these small-scale local manufacture systems might not necessarily lead to a more sustainable production system. In this paper, “the honeycomb model” is proposed as a computational framework for the simulation and optimization of manufacturing and distribution of fast moving consumer goods (FMCG) from an integrated techno-economic and environmental point of view. The manufacturing of tomato paste has been chosen as representative case study, and a systematic evaluation of optimum manufacturing configurations under different scenarios has been performed. The results of this analysis indicate that a shift towards a favorable distributed manufacturing is obtained in systems with large product demand and/or located at regions of big size, while centralization of production is favorable in systems with relatively small product demand and/or located at regions of modest size. In addition, centralized manufacturing is favored when there are significant differences in the carbon footprint of the raw materials depending on their origin. Overall, the honeycomb model can be used as a method to assess financial and environmental sustainability impact of alternative manufacturing scenarios for different FMCG's.

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1. Introduction

The Fast-Moving Consumer Goods (FMCG) sector, which includes household and personal care products as well as processed foods and beverages, is one of the most important industrial sectors worldwide. During past decades, FMCG manufacturers based their competitiveness on achieving economies of scale – i.e. expanding their production to reduce manufacturing costs. This has resulted in centralized production systems (Brodt et al., 2013), in which large areas are served by a single facility and complex, expensive supply chains. However, current environmental and climate change

policies (e.g. Europe, 2020 Strategy, UK Climate Change Act, COP21 Climate Agreement), together with consumers' demand for more eco-friendly products (Kremer et al., 2016; Edwards-Jones et al., 2008; Weber and Matthews, 2008) have exposed the sustainability limitations – economic, social and environmental – of such large supply chains (Hutchins and Sutherland, 2008; Cholette and Venkat, 2009).

In this context, *distributed* or *local* supply chains have emerged as an alternative (Srai et al., 2016) to reduce transport costs and GHG emissions and to satisfy consumers' eco-demands. The increasing interest for decentralized production systems is based on a series of factors such as flexibility in the manufacturing of other products, adaptation to local preferences/demands (O'Hara and Stagl, 2001; Erenguc et al., 1999), better local communication between customer and producer and faster decision-making (Garrehy, 2014), customer perception of freshness in the case of food products and the reduction of the inventory of immediate

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consumption goods (Akkerman et al., 2010; Erenguc et al., 1999). De-centralization has been proposed as a viable solution specifically for biomanufacturing. (Clomburg et al., 2017). Within the wider context of manufacturing there has been an anticipation that distributed systems will deliver significant environmental benefits (Kohtala, 2015; Kohtala and Hyysalo, 2015), which are expected to be more relevant in developing markets (Rauch et al., 2016).

The supply chain for distributed manufacturing faces, however, several challenges to be sustainable and competitive versus a centralized production chain. A larger capital investment is required for multiple processing plants and energy use (Mundler and Rumpus, 2012), inventory and production scheduling are less efficient than for centralized production (Erenguc et al., 1999). Strategies to improve the competitiveness of distributed manufacturing range from reducing dependence on non-renewable resources (Ziesemer, 2007); improvement of logistic networks (Coley et al., 2009) and the technology used for small production capacities (O'Hara and Stagl, 2001); reduction of (food) product waste due to the expiration date or quality lost (Hsu et al., 2007); reduction of the number of intermediaries in the supply chain (O'Hara and Stagl, 2001) and transport distances. Digital technologies, e.g. cloud manufacturing services, have been also proposed to explore the opportunities offered from a decentralized manufacturing system (Zhang et al., 2017).

In this context, the food chain represents a good example of this shift in the manufacture paradigm. Questions like if the resource efficiency can be improved by a local (and distributed) manufacturing of the product or how to assess the ways in which an environmentally and socially sustainable food system is also economically feasible have become priority for food chain actors (Ingram et al., 2013). It should also be noted that a large value of the “food miles” (Smith et al., 2005) has been associated with a greater environmental impact for transporting raw materials/products, and thus with a higher carbon footprint of the final product. Food transport represents 180 ktons of CO₂ emissions in UK (Smith et al., 2005), and 89.9 million tons in USA (Weber and Matthews, 2008). The transport of vegetable/fruit products represents 18% of the total GHG emissions of the supply chain (DFAT). Besides, according to Smith et al. (2005) the cost associated to social and environmental impacts of the food transportation in UK (e.g. traffic congestion, air pollution, accidents) is equivalent to 12.2 billion USD (9 billion GBP) per year. On the consumers' side, this has been reflected on the general perception that “locally produced” foods present higher quality, are environmentally friendly and also contribute to strengthen the local communities (Paloviita, 2010; Edward-Jones et al., 2008), which has led, for example, to the recent rise of craft beers (Kleban and Nickerson, 2011).

The environmental impact of a food (FMCG) supply chain depends on several factors and minimizing food miles – i.e. shorten the supply chain - might not always go hand in hand with the minimization of the chain's total CO₂ emissions (Smith et al., 2005; Jones, 2002). The economic and environmental assessment of the food chains is a multi-factor problem that includes the local supply capacity of raw material(s), local energy and water resources, fuel efficiency of the transportation means, the size of the manufacturing plant(s), labor costs and the taxation regime of the region (Cottee et al., 2016; Brodt et al., 2013; Cachon, 2011). For food supply chains in particular, the environmental analysis of Weber and Matthews (2008) suggests increasing the vegetables and fruit proportion in the consumer diet to reduce the amount of food groups that have greater GHG, e.g. red meat and dairy. Further optimization of a (food) supply chain can consider aspects such as price uncertainty (Hodder and Dincer, 1986), operational cost (Haug, 1992), social indicators (Mota et al., 2015; Veldhuizen et al., 2015) efficiency in scheduling process and the environmental

impact (Guillen-Gosalbez and Grossmann, 2009). See Aslam et al. (2011) and Meixell and Gargeya (2005) for a relevant review.

The decision to move from centralized to distributed/local manufacture is thus complex, and requires a systematic scenario evaluation. This paper suggests one possible approach, by constructing a mathematical framework through which different supply chain scenarios can be assessed hence offering a two-fold contribution:

- (i) an economic and environmental assessment of the impact of a local/distributed production vs. a centralized production on the design of a food supply chain (as example of FMCG chain),
- (ii) an analysis of the main factors (e.g. size of the geographical region, product demand, or supply capacity) that can shift an optimum configuration from a centralized production to a more distributed one.

To that purpose, a platform – called the *Honeycomb model* – has been developed to evaluate different chain scenarios in FMCG systems with specified product demand and raw material capacity. The *Honeycomb model* has been constructed to incorporate a mixed integer non-linear optimization problem (MINLP), where the objective is to minimize processing and transportation costs as well as CO₂ emissions from the farm gate to the distribution center.

In this work, a vegetable-based product, i.e. tomato paste, has been chosen as a case study, as it constitutes the most commonly used FMCG food product (Soufyan et al., 2016) - only in the USA, one of the biggest tomato producers (FAOSTATS), the tomato paste consumption is 1.07 million tons per year (Morning Star, 2016), while the world production and consumption of tomato products is about 41 million tons per year (Agrotipos, 2016). The evaluation of different chain scenarios presented here will define those cases in which a decentralized tomato paste production becomes a favorable manufacturing system. This approach becomes particularly relevant in the context of EU initiatives promoting the development of short supply chains and of local food systems (Augère-Granier, 2016). In addition, this case study gives an illustrative example on how evaluating the carbon footprint of the raw material locally - or non-locally - sourced can affect supply chain design.

The paper is organized as follows. The formulation of the Honeycomb model is presented in Section 2, where the tomato paste process and the basis for the economic and environmental analysis are also defined. Section 3 presents the optimum chain configurations for the different scenarios evaluated and discusses the effect of the main factors affecting the supply chain. Finally, conclusions are presented in Section 4. In the Supplementary Material all the model assumptions as well as complete details on the calculations of the process costs and CO₂ emissions are collected.

2. Methods

Food supply chains consist of several stages of production, distribution and storage from the raw material producers to the final consumer. Three actors can be involved in the distribution (and storage) of food products to the consumer: wholesaler, retailer, and foodservice, or the products can be directly sold to the consumer (Akkerman et al., 2010).

Here, a *farm gate to distribution center* approach has been adopted for the economic and environmental analysis of the tomato paste supply chain. It has been assumed that the raw material – i.e. tomatoes – is grown in farms from where it is transported to the processing plants. In these plants, the tomato paste (TP) is processed and canned, then is subsequently transported to the wholesaler using a single distribution step, i.e. the product is

delivered either to the logistic center or (as assumed in this paper) directly to regional Distribution Centers (DC). The optimum manufacturing configuration that minimizes the cost and environmental impact of the product includes the number, location and capacity of the factories, and is computed using the *honeycomb model* for each scenario analyzed. A description of the tomato paste process and the *honeycomb model* are given in the following sections.

2.1. Tomato paste process

The steps involved in the manufacture of tomato paste (Karakaya and Ozilgen, 2011; Saravacos and Kostaropoulos, 2002) are illustrated in Fig. 1. The process starts with the reception of the tomatoes from the farms. The tomatoes are washed by a water spray system while transported on rollers to the sorting table, where the unripe or spoiled tomatoes are discarded. After this, the ripe and clean tomatoes are crushed, and the pulp is heated up to 93 °C in a process called *hot break*. The hot pulp is then passed to a pulper or refiner, where the seeds and skin are separated from the juice. The tomato juice – initially with a concentration of 6 %w/w of total solid (equivalent to 6 °Brix) – is concentrated in a three-effect evaporator up to a concentration of 32%w/w (32 °Brix). The tomato paste obtained from the evaporator is sterilized (105–106 °C for 90s), and then the paste is cooled down to 35–38 °C prior to being canned in pre-sterilized steel cans (Maroulis and Saravacos, 2008). TP cans of 0.41 kg are packaged in cardboard boxes with capacity for 24 TP cans. All other process assumptions are summarized in Appendix A of the Supplementary material.

The tomato paste process described above was simulated using SuperPro Designer (see process flow diagram in Fig. 1). The mass and energy balances as well as the equipment sizing obtained from the simulation were used for the economic and environmental analysis of the supply chain and its further optimization. Product losses were neglected, while a cost for the treatment of process water was included in the economic analysis, which is presented in Appendix B of the Supplementary material.

2.2. Economic analysis

The operational cost per kg of TP (C_{op}) is estimated using process simulation (implemented in the platform SuperPro) as a function of the raw material required, energy consumption, equipment as well as capital and transport costs. Since the TP production can be carried out in one or several manufacturing plants, C_{op} can be expressed as:

$$C_{op} = \frac{\sum_i C_{ac,i}}{\sum_i P_i} \quad (1)$$

where $C_{ac,i}$ is the total annualized cost (in USD yr⁻¹), and P_i is the annual tomato paste production (in kg_{TP} yr⁻¹) of plant i . $C_{ac,i}$ is given by the sum of the manufacturing cost (C_M), the transport cost (C_T), and the annualized capital cost (C_C), whose values are computed following the methodology described in (Maroulis and Saravacos, 2008) and summarized in Appendix B, as well as the parameters and assumptions used.

The plant investment was computed using the Lang method (Peters et al., 2004), while the equipment cost was estimated as a function of its size/capacity using the Guthrie equation (Maroulis and Saravacos, 2008) (see Appendix B).

2.3. Quantification of CO₂ emissions

The total CO₂ emissions per kg of TP produced (CO_{2T}) can be decomposed into three main components: agriculture, process and transportation:

$$CO_{2T} = CO_{2agriculture} + CO_{2process} + CO_{2transport} \quad (2)$$

As in the cost estimation, the quantification of the CO₂ emissions is based on the materials/energy required for the tomato paste production, and the CO₂ emissions factors related to each activity and/or the production of the raw materials/utilities. The equations and parameters used for the estimation of each CO₂ component can be found in Appendix C.

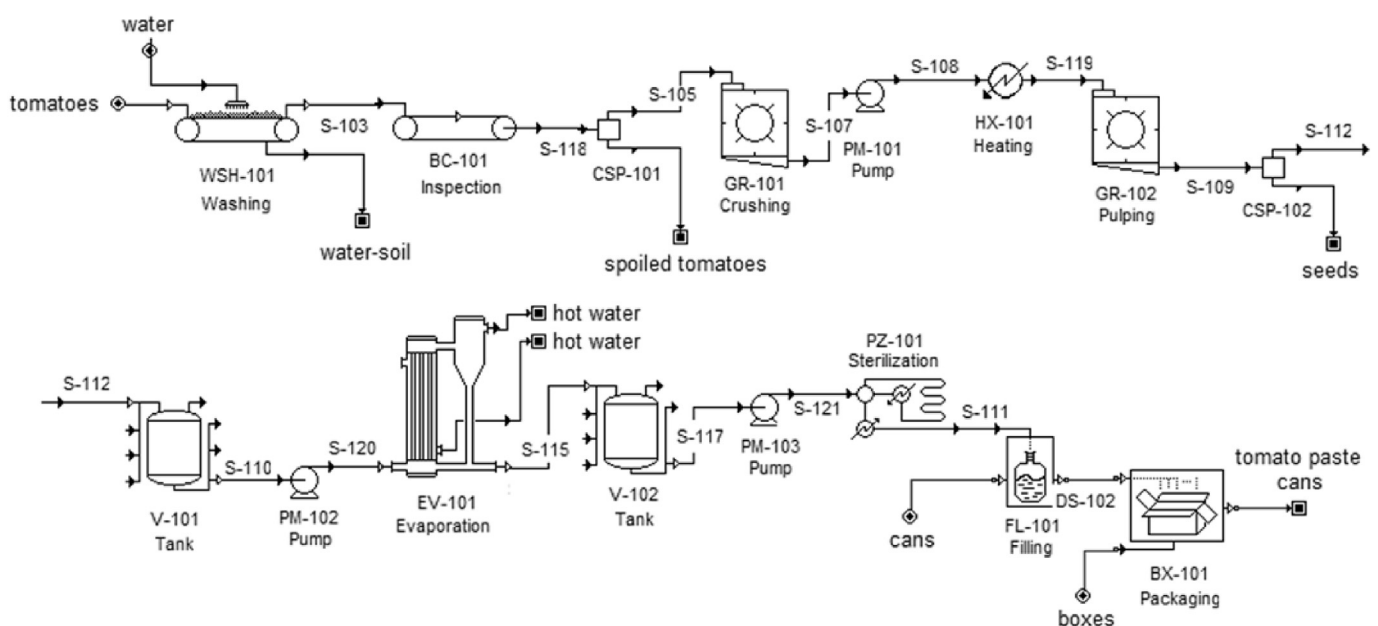


Fig. 1. Tomato paste production flowsheet developed in SuperPro Designer. The hot water streams leaving the evaporator and the pasteurizer are cooled down in a cooling tower (not showed in the diagram), and then re-used for washing step.

2.4. Honeycomb model

The design of a manufacturing supply chain is a multi-factor problem. In this section, a computational framework - the *Honeycomb model* - is presented as a tool to assess those relevant scenarios that can influence the sustainability and profitability of the supply chain.

In the *Honeycomb model* the geographic region to analyze - of area A_T - is divided into a number of hexagonal cells, N_{cell} (Fig. 2A), of size A_{cell} , whose sides a_{cell} , b_{cell} , and c_{cell} (Fig. 2B) can be estimated as:

$$a_{cell} = c_{cell} = \sqrt{\frac{2A_{cell}}{3\sqrt{3}}} \quad (3)$$

$$b_{cell} = \frac{\sqrt{3}a_{cell}}{2} \quad (4)$$

To show the potential of the honeycomb model, but maintaining simplicity, in the case presented in this work, we have considered $N_{cell} = 10$. This number of cells is big enough to study and compare a centralized production vs. a distributed one.

The processing plants i , farms j and distribution centers k can be located in any of the sides and/or center of the hexagons, i.e. positions pa , pb , ..., pm in Fig. 2A. The distance between two facilities (i.e. $D_{j,i}$ or $D_{i,k}$) is given by the length of the connecting straight-line. Here, we assume that the transporting truck from point 1 to point 2 makes the round trip, e.g. a truck that transports tomatoes from j to i will travel $2D_{j,i}$. However, the food miles are estimated as the average distance (in a single trip) travelled by the raw material plus the final product, this is:

$$FoodMiles = \frac{\sum_j \sum_i D_{j,i} n_{j,i} + \sum_k \sum_i D_{i,k} n_{i,k}}{\sum_i P_i} \quad (5)$$

where $n_{j,i}$ and $n_{i,k}$ are the number trucks required to transport tomatoes and TP cans, respectively, between two facilities.

Once the location of the facilities is defined, then the optimum supply chain configuration can be computed by solving an optimization problem aiming to minimize the cost and the CO₂ emissions of the whole process. For that, the *Honeycomb model* is employed to formulate a single-objective MINLP optimization problem of the form:

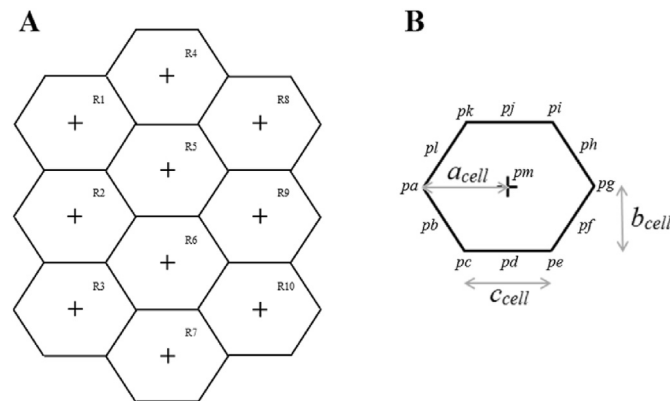


Fig. 2. Honeycomb model. (A) The system is divided in 10 hexagonal regions. (B) Dimensions of the each hexagonal region (a_{cell} , b_{cell} , and c_{cell}) and the possible position (pa , pb , ..., pm) of the farm, processing plant, and distribution center facilities.

$$\text{minimize } C_{apparent} = C_{op} + Price_{CO_2} CO_{2T} \quad (6)$$

s.t.

$$Z_i \cdot P_i = \sum_k X_{i,k} \quad (7)$$

$$Z_i \cdot P_i = \sum_j Y_{i,j} / Yield_{T/TP,j} \quad (8)$$

$$dDC_k = \sum_i X_{i,k} \quad (9)$$

$$F_j \geq \sum_i Y_{i,j} \quad (10)$$

$$\sum_i Z_i \leq NoP \quad (11)$$

$$0 \leq P_i \leq \sum_k dDC_k \quad (12)$$

$$0 \leq X_{i,k} \leq \sum_k dDC_k \quad (13)$$

$$0 \leq Y_{i,j} \leq F_j \quad (14)$$

$$\begin{aligned} Z_i &= 0 \quad \text{when } P_i = 0 \\ Z_i &= 1 \quad \text{otherwise} \end{aligned} \quad (15)$$

where the objective function $C_{apparent}$ (Eq. (6)) is the apparent product cost, and is given by the sum of the operational cost per kg of product and a penalty price ($Price_{CO_2}$) per kg of CO₂ produced during the manufacturing and distribution of 1 kg of product. The variables C_{op} and CO_{2T} in Eq. (6) are computed using the equations given in Section 2.2 and Section 2.3, respectively.

The inputs of the model are: the price of the raw materials and utilities, the transport cost, the CO₂ emissions factors, the rate of material and utilities required in the process, as well as some restrictions of the system, such as the distance between the facilities (which are proportional to the size of the system A_T), the demand of product by each DC, and the availability of the raw material.

The capacity of each plant (P_i , in P_i kg_{TP} yr⁻¹) must satisfy totally or partially the demand of product of all/some distribution centers which is represented by Eq. (7), where the amount of TP produced in plant i must equate the TP sent to every DC k , i.e. $X_{i,k}$ (in kg_{TP} yr⁻¹). Similarly, Eq. (8) indicates that the fresh tomatoes required by plant i can be supplied for one or more farms j , where $Y_{i,j}$ (in kg_{Tomato} yr⁻¹) is the amount of tomatoes sent to plant i from farm j . The ratio between the kg of tomatoes required to produce 1 kg of TP (Eq. (8)) is represented by the yield $Yield_{T/TP,j}$ (in kg_{Tomato} kg_{TP}⁻¹), this parameter is related to the quality of the raw material, in this case the °Brix of the tomatoes from farm j (this value varies between 4 and 6 °Brix). The higher the tomato's °Brix, the fewer tomatoes will be required to produce TP with 32 °Brix. In this work, we assume that all farms produce tomatoes of 6 °Brix, and the $Yield_{T/TP,j}$ value is computed from the process simulation results.

Eq. (9) indicates that the amount of product from all plants i ($X_{i,k}$) must satisfy the demand of DC k (dDC_k , in kg_{TP} yr⁻¹), in this case we assume the total product demand is satisfied, but there is not an over production of TP, thus Eq. (9) is an equality constraint. On the other hand, the inequality constraint of Eq. (10) restricts the

availability of raw materials, i.e. the amount Y_{ij} supplied to all plant i from farm j should not exceed the maximum capacity of each farm j (F_j , in $\text{kg}_{\text{Tomato}} \text{yr}^{-1}$).

The integer variable Z_i in Eqs. (7), (8) and (11) indicates the presence of plant i ($Z_i = 1$), i.e. when $P_i > 0$, or its absence ($Z_i = 0$) when $P_i = 0$. Eq. (11) restricts the total number of plants in the system to a maximum value Nop given by the user as a parameter. The maximum number of plants Nop allows investigating different scenarios in a centralized or distributed production.

In this formulation, P_i , $X_{i,k}$, $Y_{i,j}$ are continuous variables that can take any value within the limits given by the user. In this example, we set the lower limit of these three variables to zero, while for the variables P_i and $X_{i,k}$ the upper limit (Eqs. (12) and (13), respectively), was set equal to the total product demand of the whole system (i.e. $\sum dDC_k$, here we assume that dDC_k is the same for all DC k), while the upper limit for variable $Y_{i,j}$ is equal to the maximum farm capacity F_j (Eq. (14)). Finally, the integer variable Z_i can take a value zero or one (Eq. (15)).

The optimization problem given by Eq. (6)–(15) was implemented and solved in Matlab using the MINLPsolver BNB20 (Kuipers, 1998; available in www.mathworks.com/matlabcentral). The Matlab program was linked with the process simulation in SuperPro to facilitate the multiple function evaluations required during the optimization.

Due to the nonlinear nature of the problem posed by the honeycomb model, the search of the global minimum is a computationally expensive task. As with other nonlinear solvers, the efficiency of BNB20 depends on the initial guess chosen.

Thus, in order to reduce the computational time required to solve the optimization problem and increase the probability to find the global optimum, we propose a linearized optimization problem (LP) whose solution will be used as initial guess for the honeycomb model. See Appendix D for the LP problem used in the estimation of the initial guess.

3. Results and discussion

In this section, the Honeycomb model is used to analyze different scenarios and their impact on the optimum design of the manufacturing supply chain. As base case, we assume a geographic region of similar size to the USA, i.e. 10 hexagonal cells (Fig. 2A) of size $A_{\text{cell}} = 914759 \text{ km}^2$, where the sources of raw material (i.e. the farms) are located at positions pa , pc , pe , pg , pi , and pk of each hexagon (Fig. 2B). Here we assume a uniform farm production in order to analyze the potential of a distributed tomato paste manufacturing, despite the fact that the production capacity of tomato depends on the geographic region, so for example California produces 95% of the processed tomatoes in USA (Morning Star, 2016). The maximum production capacity of each farm is set to $28\,619 \text{ ton}_{\text{Tomato}} \text{yr}^{-1}$. A total of 10 DCs are considered and located at position pm , each one with a demand of $10\,754 \text{ ton}_{\text{TP}} \text{yr}^{-1}$, which corresponds to 10% of the USA tomato paste production in 2015 (Morning Star, 2016). Processing plants can be built at every side of the hexagon, i.e. positions pb , pd , pf , ph , pj , and pl (Fig. 2A), whose capacities and final position will be computed by solving Eq. 6–15. These assumptions hold for all simulations unless otherwise stated.

3.1. Effect of the penalty price for CO₂ emissions

The price per kg of CO₂ produced, $Price_{\text{CO}_2}$, has been defined as a penalty function that determines the importance given to the reduction of CO₂ emissions over the cost reduction. Therefore, when $Price_{\text{CO}_2} \rightarrow 0$ the second term of Eq. (6) disappears and the honeycomb model will predict the supply chain configuration with the lowest operational cost, while for $Price_{\text{CO}_2} \rightarrow \infty$ the first term of

Eq. (6) is negligible compared to the second term, and then the configuration computed will be the one with the lowest CO₂ emissions.

Fig. 3 shows the operational cost (diamond line, computed using $Price_{\text{CO}_2} = 0$) and the CO₂ emissions (square line, computed using $Price_{\text{CO}_2} \rightarrow \infty$) obtained for different numbers of processing plants in the system. The minimum operational cost is found when the number of plants is 6, while the minimum CO₂ emissions corresponds to 16 plants (see Fig. 3). As results indicate, centralization results in lower costs, while a more distributed production favors a reduction of the CO₂ emissions since the transportation distances are shorter.

When no transportation is considered - i.e. when only the agriculture and process components of the CO₂ emissions are taken into account - manufacturing in a plant with a capacity of $1000 \text{ ton}_{\text{Tomato}} \text{h}^{-1}$ results in CO₂ savings of only $0.052 \text{ kg}_{\text{CO}_2} \text{ kg}_{\text{TP}}^{-1}$ compared to the emissions of a $1.1 \text{ ton}_{\text{Tomato}} \text{h}^{-1}$ plant. These savings are related mainly to the process component, and show that the reduction of the CO₂ emissions per kg of product does not benefit particularly from the economies of scale in this particular case. However, higher CO₂ savings can be obtained in food processes where the energy efficiency of the equipment (per kg of product) is significantly improved at higher capacities.

According to the European Energy Exchange, the cost per kg of CO₂ produced is 0.0056 USD. However, the use of $Price_{\text{CO}_2} = 0.0056 \text{ USD kg}_{\text{CO}_2}^{-1}$ results in the prediction of an optimum number of plants equal to 6, with no reduction of the CO₂ emissions compared to the case $Price_{\text{CO}_2} = 0$. The use of an appropriate $Price_{\text{CO}_2}$ value would allow finding the optimum configuration (with a number of plants between 6 and 16) that effectively reduces CO₂ emissions compared to those produced in a system with 6 plants (i.e. $138174.4 \text{ ton year}^{-1}$, see Fig. 3), but without a significant increase in the operational cost (estimated as $1.87 \text{ USD kg}_{\text{TP}}^{-1}$ for 6 plants). To find such value of $Price_{\text{CO}_2}$, a sensitivity analysis was performed, showing that the optimum number of plants approaches to 16 when the penalty cost $Price_{\text{CO}_2}$ increases (see Fig. 4). In particular, a $Price_{\text{CO}_2}$ value of $1.008 \text{ USD kg}^{-1}$ shifts the optimum number of plants to 9, where the CO₂ emissions are reduced by 10% compared to those estimated for the case $Price_{\text{CO}_2} = 0$ (for 6 plants) of Fig. 4 (it should also be noted that the supply chain configuration with 16 plants represents a CO₂ reduction of 15%), while the product cost increases $0.085 \text{ USD kg}_{\text{TP}}^{-1}$. In order to effectively reduce the carbon footprint of the product, we use $Price_{\text{CO}_2} = 1.008 \text{ USD kg}^{-1}$ for the subsequent simulations. This $Price_{\text{CO}_2}$ value agrees with the results found by Cachon (2012), which indicate that the minimization of cost and

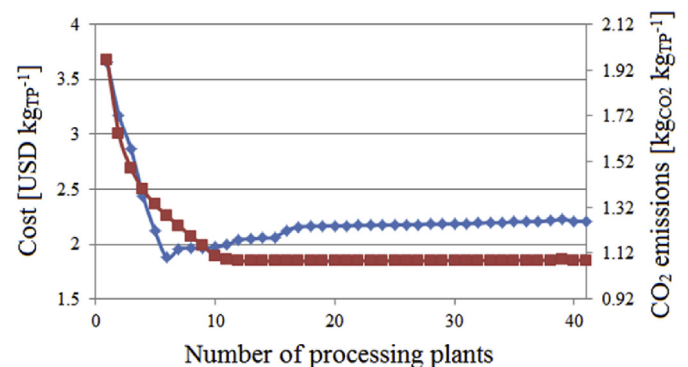


Fig. 3. Apparent cost as a function of the number of plants in the honeycomb system. The optimum manufacturing configurations that minimize the apparent cost C_{apparent} are computed for two different cases $Price_{\text{CO}_2} = 0$, where $C_{\text{apparent}} = C_{\text{op}}$ (diamond line), and $Price_{\text{CO}_2} \rightarrow \infty$, where $C_{\text{apparent}} = C_{\text{O}_2T}$ (square line).

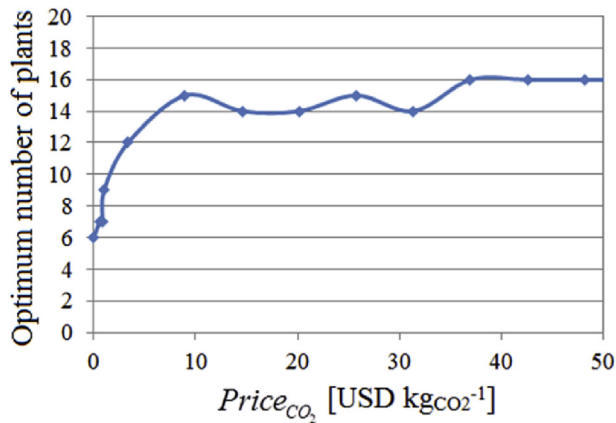


Fig. 4. Optimum number of plants in the honeycomb system computed for different $Price_{CO_2}$ values.

CO₂ emissions in a supply system of retail stores and the consumer homes can be achieved only with penalty cost $Price_{CO_2}$ values above 1 USD kg⁻¹.

3.2. Effect of the number of alternative plant locations in the honeycomb system

One of the factors that can affect the optimum design of a food chain is the number of alternative locations for the processing plants, these possible locations are given by the user to the honeycomb model. In our base case study, a maximum of 41 plants can be located in the honeycomb system (specifically at positions pb , pd , pf , ph , pj , and pl of each hexagonal cell, see Fig. 2A). The number of alternative plants can be easily increased by increasing the number of hexagonal cells (N_{cell}) in which the system is divided. In this section, we analyze the influence of N_{cell} on the optimum manufacturing configuration. For this, we assume that each hexagonal cell of our base case denoted as $S1$, with $N_{cell} = 10$ (blue hexagon in Fig. 5A), is subdivided in 4 regular hexagons (black hexagons in Fig. 5A), thus the original system is now divided in $N_{cell} = 46$, called scenario S2 (Fig. 5B). In order to make fair comparisons among different N_{cell} , the farms and distribution centers are located in the same positions as in scenario $S1$ (indicated by blue hexagons in Fig. 5B), while the plants can be located on the sides of each black cell (see triangles in Fig. 5A) in the dashed region indicated in Fig. 5B. Therefore, the number of farms and DCs is the same for both $S1$ and $S2$ scenarios, but the maximum number of plants for $S1$ is 41 plants, while for $S2$ is 131 plants. Similarly, a third scenario $S3$ with $N_{cell} = 123$, is defined by subdividing each hexagon of our base case $S1$ in 9 hexagonal cells (black hexagons in Fig. 5C), thus the maximum number of plants in $S3$ is equal to 281.

The comparison of the optimum number of plants computed for three scenarios (9 plants for $S1$, 9 plants for $S2$, and 10 plants for $S3$) indicates that for this case study the optimum configuration is bounded and is not dependent on N_{cell} . Hence, there is no tendency towards fully distributed manufacturing, for higher values of N_{cell} . However, since the system is divided in more sub-regions, there are more alternative positions where the processing plants can be located, and these alternatives might be closer to the farms/DC, which would reduce the transportation distances. The results show that the food miles estimated decrease as N_{cell} increase (Fig. 6C), thus the transport cost and CO₂ emissions decrease too (Fig. 6A and B, respectively). Nevertheless, the solution of the optimization problem (Eq. 6–15) for $S2$ (computational time: 2.29 h) and $S3$ (4.01 h) become computationally more expensive than for $S1$

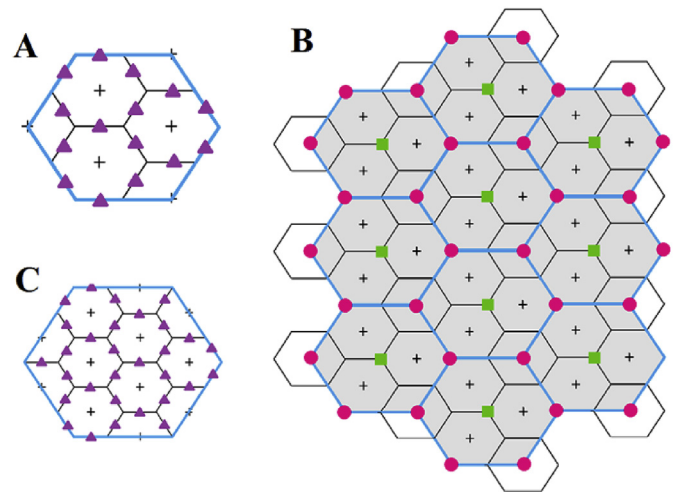


Fig. 5. Sub-division of a hexagonal cell of the scheme $S1$ (in blue) in 4 hexagons (in black) for the scenario $S2$ (A), and in 9 hexagons (in black) for $S3$ (C). The triangles represent the alternative positions where the processing plants can be located. (B) The honeycomb system for $S2$, the cells are in black color; the base case scenario $S1$ is indicated in blue color as a reference. The processing plants can be only allocated in shaded black cells. The circles and squares indicate the locations of the farms and DC, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

(1.06 h), since the number of variables (P_i , Y_{ij} , $X_{i,k}$, and Z_i) increases with the number of cells.

The purpose of this work is to identify the factors that can shift a centralized manufacturing to a more distributed one. Therefore, since N_{cell} has a negligible effect on the optimum number of processing plants, and looking to economize computing resources, the scenario $S1$ will remain the base case in the following sections.

3.3. Effect of total area A_T

Another parameter that could affect the design of the supply chain is the total area or size of the region analyzed (A_T). The results indicate that the apparent cost $C_{apparent}$, given by Eq. (6), increases with A_T (see square line in Fig. 7C), although there is not a linear relation between the optimum number of plants predicted and this area (Fig. 7A). For regions with $A_T \leq 4.5 \times 10^6$ km² (e.g. half of the size of USA) a centralized production (or a less distributed production) is more favorable despite the fact that the food miles (Fig. 7B) as well as the cost and CO₂ emissions related to the transport (cross line Fig. 7C and square line Fig. 7D, respectively) increase in a non-linear way. The shift to more distributed manufacturing is more favorable for larger countries or regions.

The impact of the travelled distances on the cost and on the CO₂ emissions, which are proportional to the size of the system, becomes more pronounced when other transportation means have to be used, e.g. airplanes are used for short life products (Edwards-Jones et al., 2008), or refrigerated transport for the case of ice cream. In these cases, high transportation cost and its corresponding CO₂ emissions could be key factors in the design of the supply chain.

3.4. Effect of raw material availability

The availability of raw material is a critical factor for the design and optimization of any process. In this case study we have assumed that all the farms have the same capacity and, although this is not necessarily true for large geographic regions where the climate conditions are not uniform, like USA (e.g. the weather in

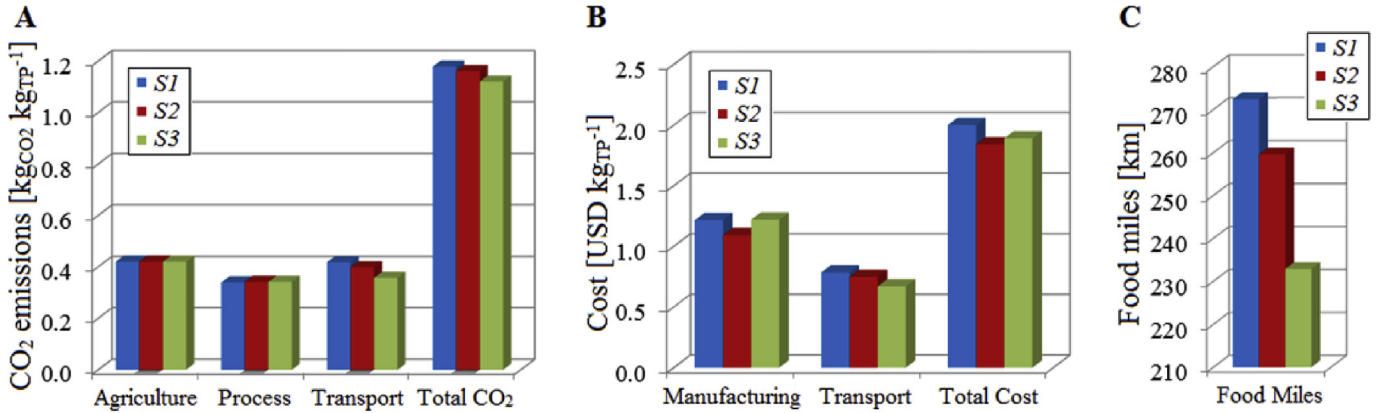


Fig. 6. Comparison of the CO₂ emissions (A), cost (B) and food miles (C) predicted for S1, S2, and S3.

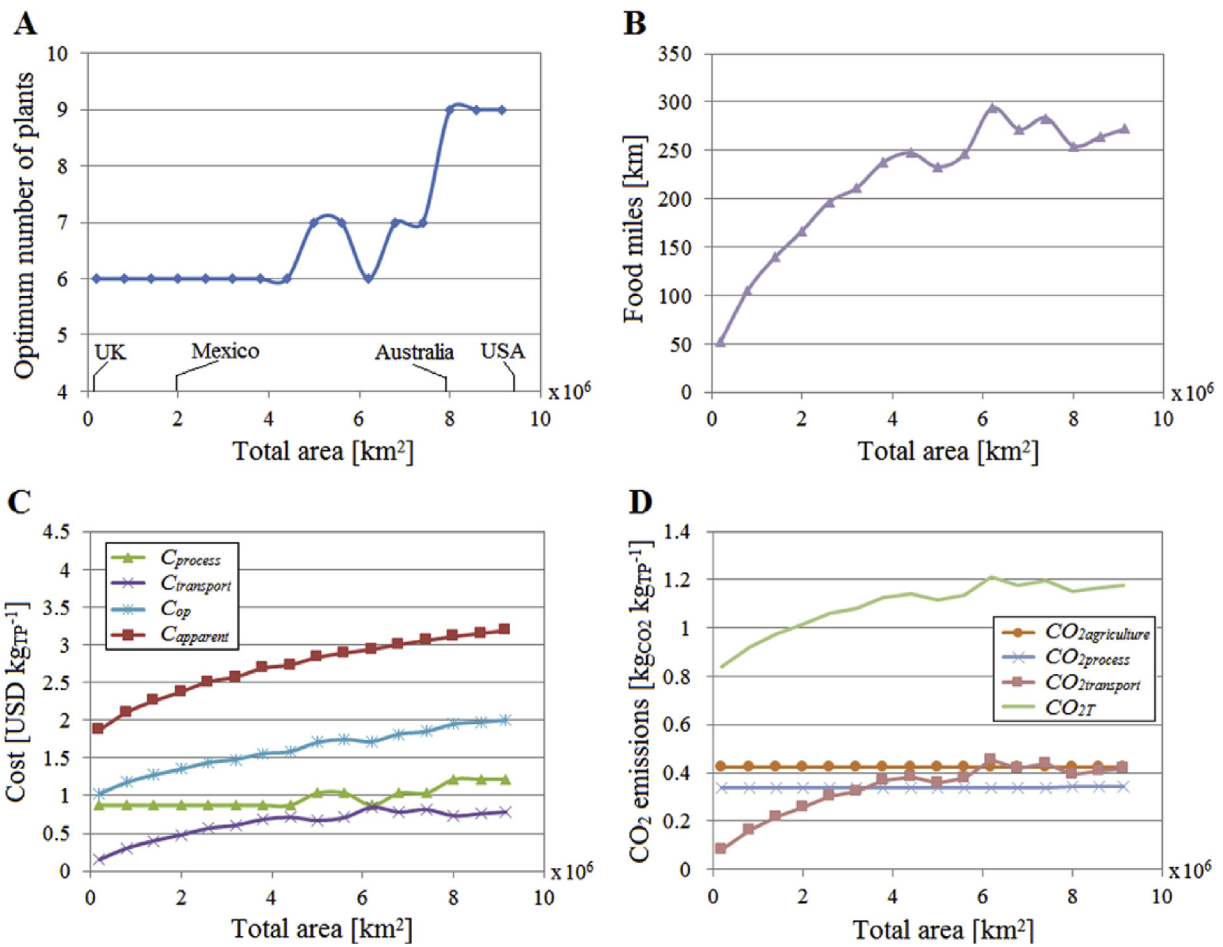


Fig. 7. Sensitivity analysis of the optimum manufacturing configuration of the honeycomb system to the total area of region analyzed. (A) Optimum number of plants. The names of some countries are added as size references of the region analyzed. (B) Food miles (C) Cost breakdown. (D) CO₂ emissions breakdown.

California would favor the cultivation of tomato more than in other colder regions), the results suggest that the local availability of raw material and its further local consumption/processing is not necessarily the most economical and environmentally friendly alternative as one would expect of a fully distributed manufacture system.

Fig. 8A and C shows the optimum number of plants and the apparent cost estimated for different farm capacities. The results reveal a trend towards centralized production for high farm

capacities, i.e. when the raw material demand of a processing plant can be satisfied by nearby farms. However, this centralization of the production converges to the same optimum number of plants equal to 6 computed when only the operational cost was minimized, i.e. the $Price_{CO_2} = 0$ case. It is interesting that in the transition zone from a more distributed production to a more centralized one (i.e. for farm capacities between 19 080 and 57 816 ton yr⁻¹), the transportation component of both cost (cross line Fig. 8C) and CO₂ (square line Fig. 8D) increases up to a maximum and then

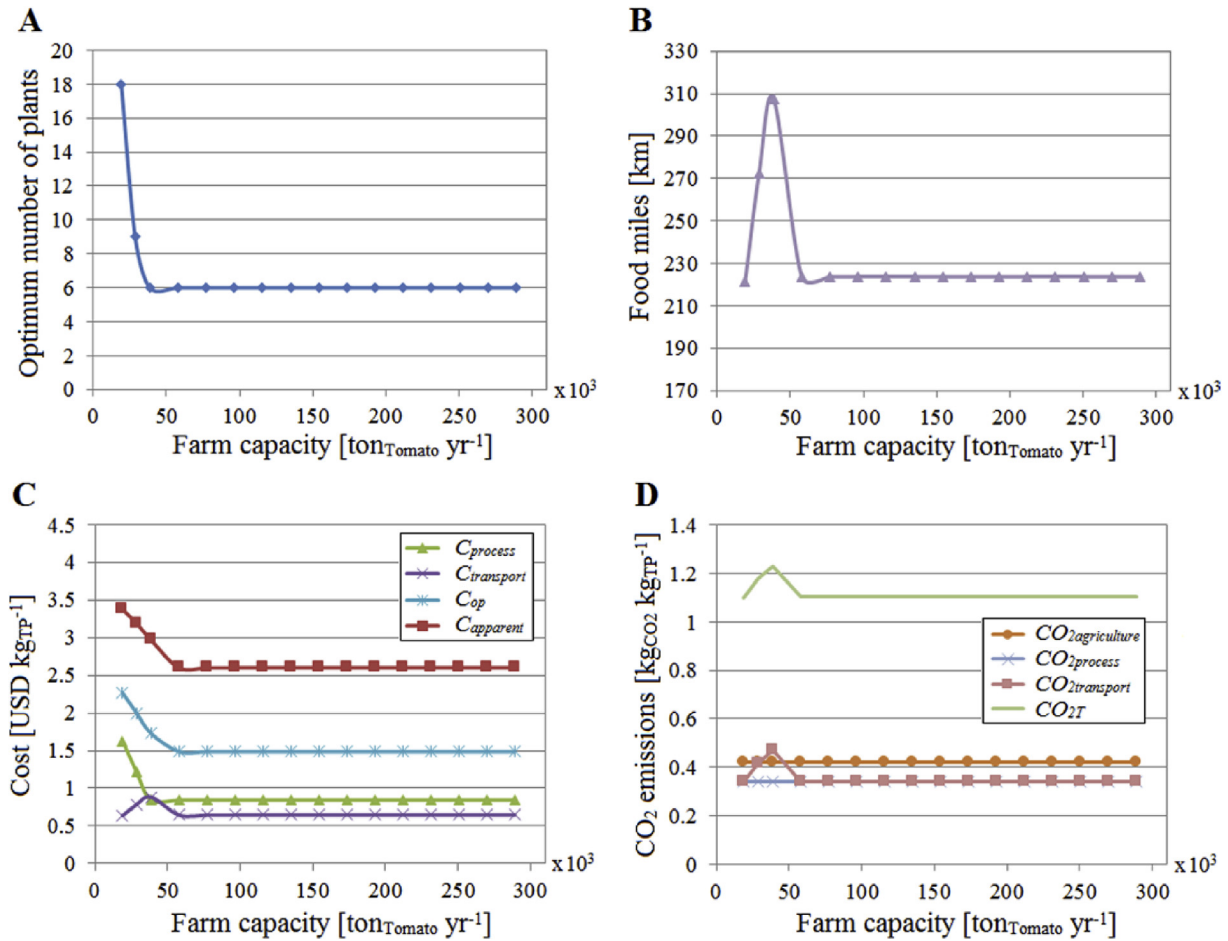


Fig. 8. Sensitivity analysis of the optimum manufacturing configuration of the honeycomb system to the tomato production capacity of each farm. (A) Optimum number of plants. (B) Food miles. (C) Cost breakdown. (D) CO₂ emissions breakdown.

decreases. This behavior is a consequence of reducing the number of plants, which increases the distances travelled from the plant to DC as reflected in the increments of the corresponding food miles (Fig. 8B). Nevertheless, these increments in transportation are balanced by the cost and CO₂ savings obtained by processing the tomato paste in plants with higher capacities, i.e. savings due to economies of scale.

3.5. Effect of product demand

Regarding the influence of the demand of the final product on the design of the supply chain, Fig. 9C shows that the apparent cost (square line) decreases when the demand grows, revealing the effect of the economies of scale on the system: the plant capacities must increase to satisfy the consumers' demand. On the other hand, the cost and CO₂ emissions associated to the transport (cross line Fig. 9C, and square line in Fig. 9D, respectively) increase since a greater number of trucks will be necessary to both supply the raw material required to satisfy the increasing demand and deliver the finished product.

In addition, by increasing the demand of the tomato paste the number of processing plants is also increased (Fig. 9A), favoring a more distributed manufacturing. For limited product demand levels, i.e. 1439.8 tonTP yr⁻¹ per DC - approx. 10% of the total UK demand of tomato paste according to Local Nexus Network; -, the centralization of the production is the most feasible option, with a predicted optimum number of plants of 2 (see Fig. 9A). Thus, the co-

operativization of the producers could be more advantageous for systems with similar characteristics.

3.6. Effect of the carbon footprint of the raw materials

Another important parameter in agro-based products is the CO₂ emitted during the production of the raw materials. Since the cultivation of tomato can be carried out in open fields or in greenhouses, the CO₂ associated to the agriculture ($e_{Tomato,j}$) can vary by several orders of magnitude. As example, the tomato cultivation in the open fields in California releases 0.0743 kg of CO₂ per kg of tomato (Herold, 2003; Albright and de Villiers, 2008), while the greenhouse cultivation in UK causes 3.1155 kg of CO₂ (Herold, 2003; Albright and de Villiers, 2008). In order to simulate a system where the farms have different sowing practices, in the next example we assume that tomatoes from the farms located in the corners of the hexagons of the dashed region indicated in Fig. 10, have CO₂ parameters $e_{Tomato,j} = 0.0743 \text{ kgCO}_2 \text{ kgTomato}^{-1}$, while the tomatoes from the other farms in the system have $e_{Tomato,j} = 0.0734 F_{agr}$ (in $\text{kgCO}_2 \text{ kgTomato}^{-1}$). Here F_{agr} is a dimensionless multiplying factor that determines the agriculture CO₂ emissions.

As shown in Fig. 11C, the apparent cost (square line) increases almost linearly with the F_{agr} -value. This is because the tomatoes from the upper region farms have a higher carbon footprint proportional to F_{agr} , which is reflected in the agriculture component of the CO₂ (dotted line Fig. 11C). However, for $F_{agr} > 1$ the optimum

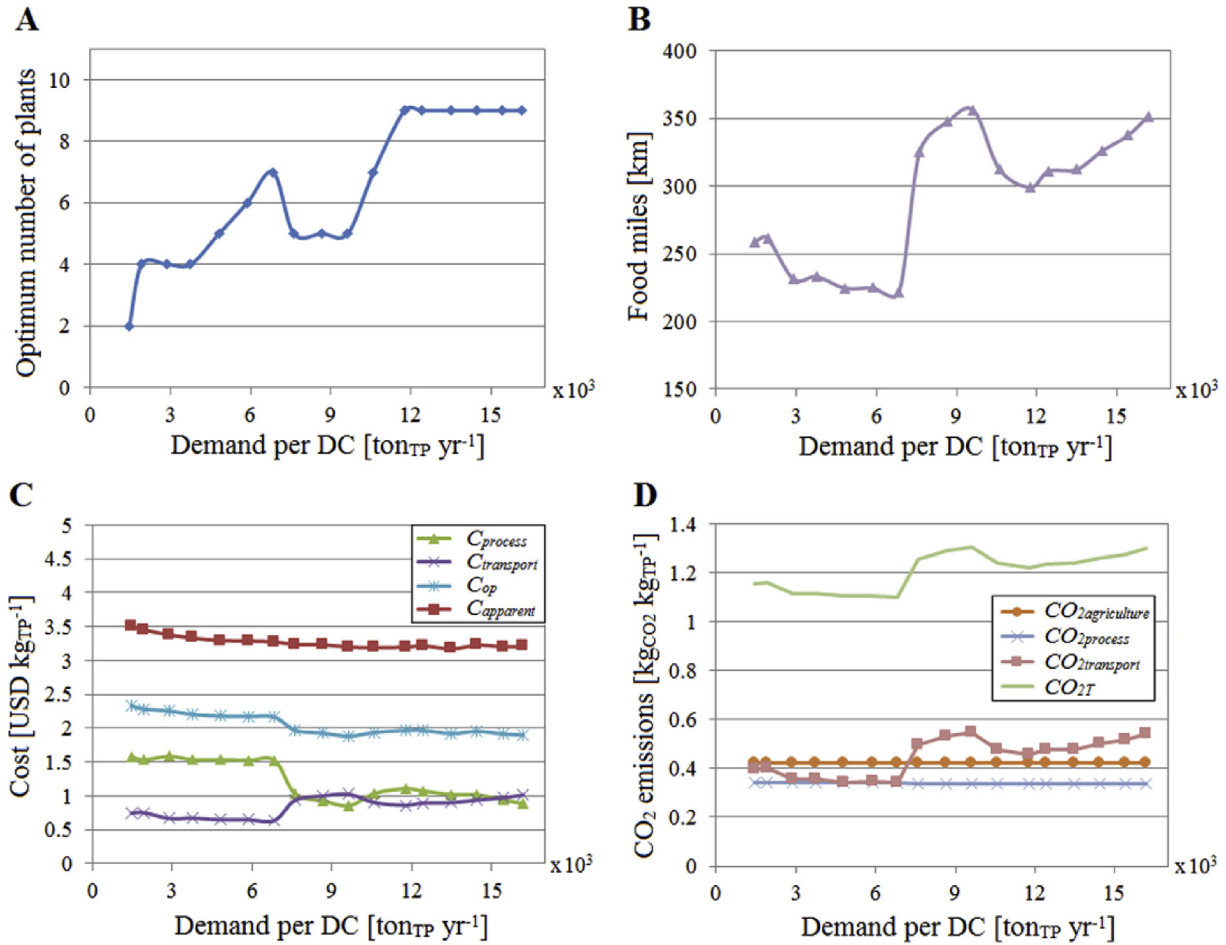


Fig. 9. Sensitivity analysis of the optimum manufacturing configuration of the honeycomb system to the TP demand of each distribution center. (A) Optimum number of plants. (B) Food miles (C) Cost breakdown. (D) CO₂ emissions breakdown.

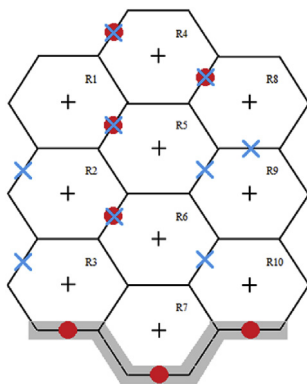


Fig. 10. Comparison of the optimum manufacturing designs for a honeycomb system where the farms have different $e_{Tomato,j}$. The Agriculture CO₂ emissions factor for farms located in the dashed region is equal to 0.0743 kg_{CO2} kg_{Tomato}⁻¹ while farms in the upper regions (not dashed) have $e_{Tomato,j} = 0.0743F_{agr}$. Circles indicate the predicted location of the processing plants for $F_{agr} > 1$, while crosses indicated the position of the plants for our base case, i.e. $F_{agr} = 1$.

configuration design shifted from 9 processing plants to 7 (Fig. 11A). A comparison of the location of these plants computed for the $F_{agr} = 1$ design (9 plants, crosses in Fig. 10) and the $F_{agr} > 1$ design (7 plants, circles in Fig. 10) shows a higher concentration of plants in

the bottom region where they can be supplied by farms with lower $e_{Tomato,j}$ (dashed region in Fig. 10). The capacity of the farms located in the dashed zone is not enough to meet the whole system demand of raw material, and thus the total production is not centralized in this zone.

As shown in Fig. 11B, when the carbon footprint of the raw material is not uniform, i.e. the $F_{agr,1} > 1$ case, the food miles computed for the optimum manufacturing configuration increase compared to the case $F_{agr} = 1$. This indicates that the optimum supply chain design is not always the one that minimizes the distance travelled by the product/raw materials, but it is the one that minimizes the total CO₂ emissions (including the CO₂ agriculture component). Therefore, the food miles concept is not necessarily a univocal parameter to assess the sustainability of the supply chain.

On the other hand, due to the symmetric nature of the honeycomb system, two optimum manufacturing configurations could be equivalent. For example, the cost and CO₂ emissions estimated for a centralized production where the processing plant is in position pa of region R1, i.e. R1 pa (see Fig. 2), would be the same that a centralized production in R10 pd . However, this possible symmetry in the results is broken when more features of the system are considered, e.g. different carbon footprint of the raw materials depending of the region of origin, as seen in the cases where $F_{agr} > 1$, where the optimum configuration comprises more processing plants in regions with lower $e_{Tomato,j}$ (shaded region in Fig. 10).

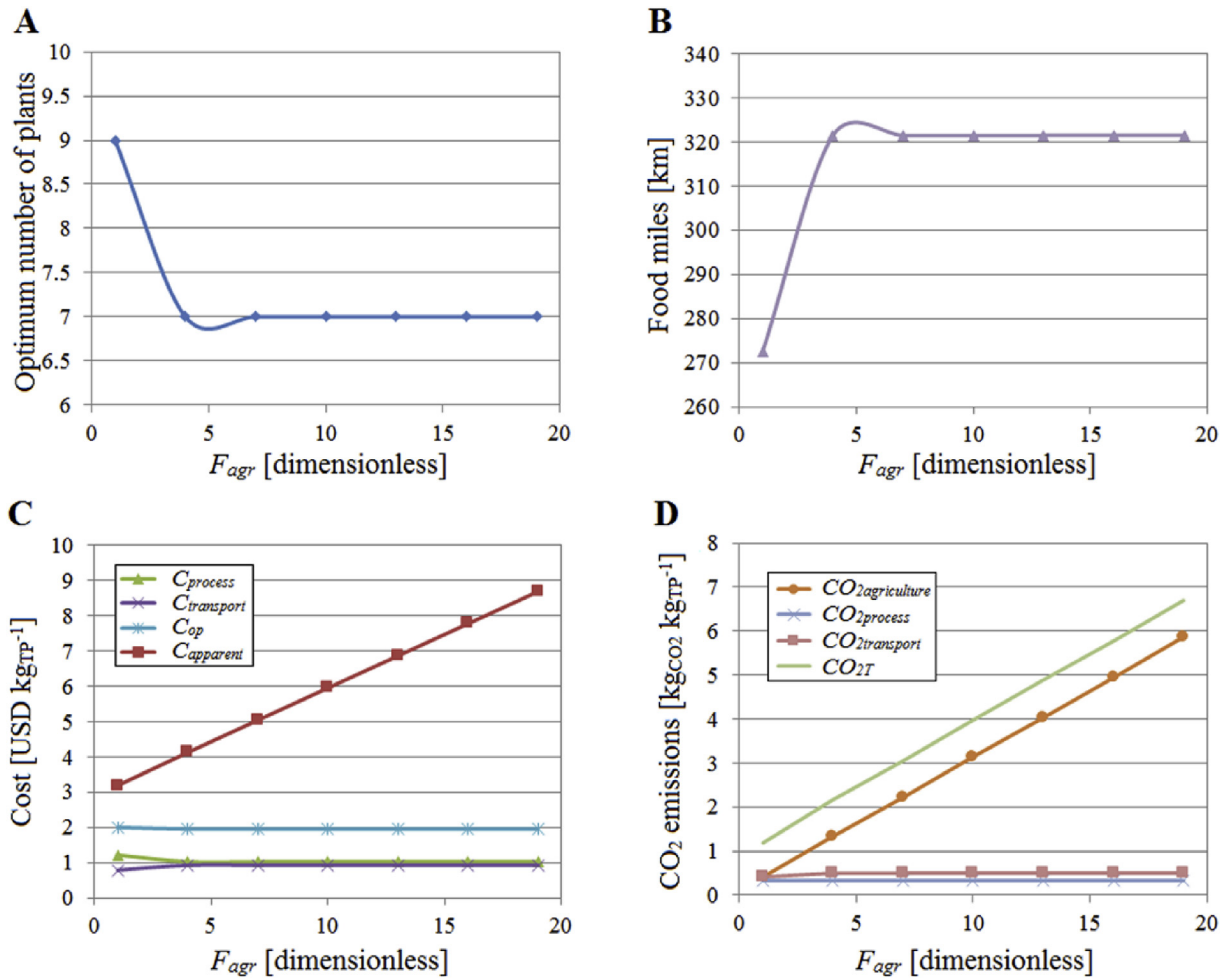


Fig. 11. Sensitivity analysis of the optimum manufacturing configuration of the honeycomb system to the agriculture CO₂ emissions factor. The multiplying factor F_{agr} determines the agriculture CO₂ emissions factor, i.e. $e_{Tomato,j} = 0.0743F_{agr}$. (A) Optimum number of plants. (B) Food miles (C) Cost breakdown. (D) CO₂ emissions breakdown.

3.7. Alternative distribution scenarios

Previous examples considered the distribution of the tomato paste from the processing plant to regional distribution centers, which is the most realistic scenario since this allows large supermarkets chains to have more control on their products and the way these will be distributed to local DC and stores (Hallsworth and Wong, 2012). Nevertheless, this common practice may cause an increase of the CO₂ emissions and transportation costs as the distance travelled from plant → DC_{regional} → DC_{local} might be significantly higher than the direct distribution from the plant to the closest local distribution centers.

In this section, we analyze two scenarios (i) the tomato paste (TP) is sent directly from the plant to the local DCs, and (ii) the TP is sent first from the plant to regional DCs, and from there to the local DCs. In addition to the assumptions made in the previous sections, we include here 51 local DCs to the system. The local DCs are located at every side and center of each hexagonal cell, i.e. positions pb , pd , pf , ph , pj , pl , and pm in Fig. 2B. The tomato paste demand of each DC_{local} is equal to 2109 ton_{TP} yr⁻¹.

A comparison of the optimum number of plants predicted for both scenarios indicates that the DC_{local} case (i.e. the direct delivery to local DCs) favors a more distributed manufacturing (11 plants), while the DC_{regional} case (i.e. the collection of the product

in regional DCs and its further re-distribution to local DCs) tends more towards the centralization of the production. This centralization of the production is reflected in a reduction of the manufacturing cost for the DC_{regional} case compared to the DC_{local} case (Fig. 12B), but it is also associated to an increment in the transportation cost for the DC_{regional} case, so that the total operational costs for both scenarios are similar (Fig. 12B).

Nevertheless, the DC_{local} scenario represents savings in the CO₂ emissions for 16 883 ton_{CO₂} yr⁻¹ (Fig. 12A), which are mainly due to the decrease of the food miles of the product (i.e. the distances travelled by the product up to the final destination, Fig. 12C) and to the corresponding reduction of the transportation component of the total CO₂ (Fig. 12A).

These results suggest that when the aim is to boost the local economies, the combination of strategies such as the direct delivery to local shops/DCs along with the co-operativization of local producers could increase the economic and environmental feasibility of a highly distributed manufacturing. In these cases, the systems can take advantages of the economy of scale not only during the processing but also in the distribution by making a better use of the capacity and efficiency of the trucks. In addition, in this case a single product was tested. When multiple products are examined a distributed manufacturing system would allow for flexible production of a larger number of variants.

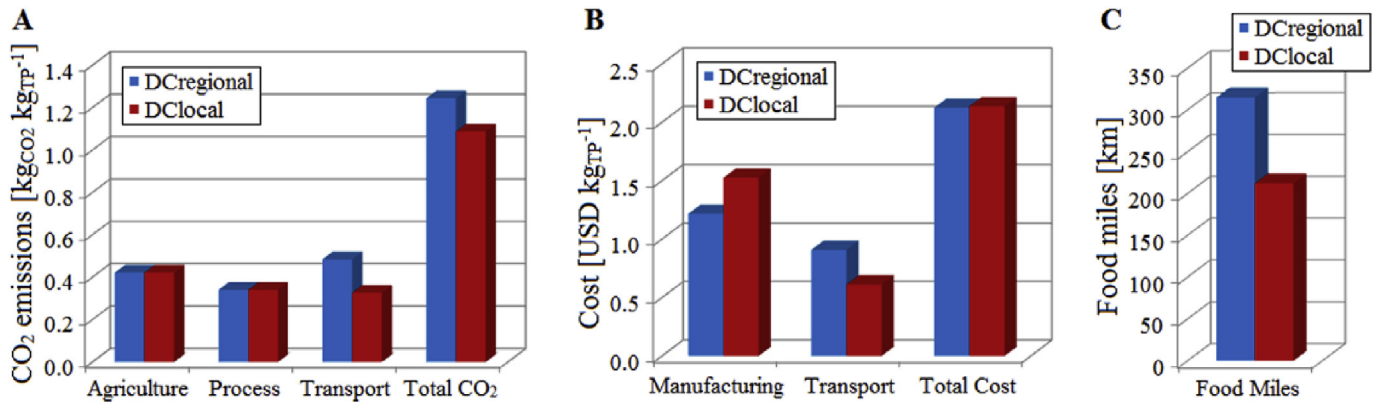


Fig. 12. Comparison of the CO₂ emissions (A), cost (B) and food miles (C) predicted for DClocal and DCregional cases.

4. Conclusions

The decision to move from centralized to distributed manufacture is a complex one. In this work, a modelling and optimization platform – the Honeycomb model – has been presented to (i) assess the economic and environmental impact of a local and distributed production vs. a centralized production on the design of a food supply chain and (ii) to analyze the role of the scale economy in the estimation of an optimum configuration design.

A series of processing and distribution scenarios for the manufacturing of tomato paste have been assessed as a function of both economic and environmental factors using the proposed *Honeycomb model*, which was established to be a flexible and robust tool to predict optimum supply chain configurations, and to determine the number, capacity and location of the processing plants, the selection of the farm(s) supplier for each plant, as well as the amount of product that has to be sent to the different DCs by each plant in the system.

The optimum configuration predicted by the honeycomb model depends on environmental factors. The results indicate that an effective reduction of CO₂ emissions associated to the process can be only achieved using high values of $Price_{CO_2}$. For the tomato paste case study a $Price_{CO_2}$ value of 1.008 USD kgCO₂⁻¹ allows the reduction 10% of CO₂. Results also suggest a trend towards a more distributed manufacturing for geographical regions larger than 450000 km² as well as for systems with a limited local availability of the raw material and/or with a high demand of the product. In the specific case of agro-based products, as is the case presented here for the manufacturing of tomato paste, the cultivation in greenhouses allows extending the availability of seasonal products; nevertheless, the carbon footprint of the raw material can increase significantly. The differences in the CO₂ emissions factors associated to raw materials shift the optimum configuration to a more centralized production.

Finally, two possible product distribution scenarios were analyzed using the honeycomb model. The results indicate the tendency to a more distributed manufacturing when the product is directly distributed to local distribution centers compared to the case where the product is sent to an intermediate and regional DC before being delivered to local shops/DC.

Although the consumption of local products is not always the cheapest or environmental friendly option, strategies such as the union of several local producers in cooperatives where processing and distribution facilities are shared can help to reduce the operational cost and the carbon footprint of local-produced goods, making them more attractive for consumers and thus favoring the local economies.

When the competitiveness of a product is based on price, as is the case for tomato paste, manufacturing tends towards a centralized system to exploit economies of scale. However, the identification of the possible scenarios that can shift the production to a more distributed one can give valuable information in light of fair-trade initiatives to favor local producers, increase the local employment rate, and reduce waste.

In other cases, for example products that require refrigeration (e.g. ice cream), perishable foods that are susceptible to damage during transportation (e.g. fresh vegetables/fruit), or where local demand requires highly customized products, the economic and environmental profitability of a distributed manufacturing is more evident. Further studies are required to analyze the factors and scenarios with greater impact on the supply chain design of these type products, for example transport temperature, different means of transportation, multi-product processes, etc.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at <https://doi.org/10.1016/j.jclepro.2018.04.075>.

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