**ORIGINAL RESEARCH**

# Sustainable supply chain network design: a study of the Colombian dairy sector

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## Abstract

The literature review shows research gaps into the food supply chain design. In that context, this paper deals with the design of a sustainable supply chain. A multi-objective mixed-integer linear programming model includes four decisions and three sustainable criteria (economic—total network costs—, environmental—carbon emissions—, and social—work conditions and societal development—). The model aims to determine the optimal location and capacity of processing and distribution facilities, to choose the suppliers from a set of potential candidates, to determine transportation modes between all the actors, and to define the quantity of product, in order to satisfy the demand of dairy products in a set of regions. The applicability of the model is tested in a realistic case in the dairy sector in the central region of Colombia. The results show the existent trade-offs between the three dimensions of sustainability. The unweighted balance results, giving more priority to the social dimension, which obtains the least deviation, affecting the environmental performance of the chain. The analysis carried out in this paper does help decision-makers that will have at hand a set of possible configurations to be chosen in order to comply with environmental and social regulations without neglecting economic performance.

## 1 Introduction

Traditional approaches for supply chain design have focused on the optimization of economic (e.g., cost) and productive related metrics (Guarnieri & Trojan, 2019). However, the sustainable development goals (SDGs) pressure the firms to adopt sustainability (Modgil

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et al., 2020). In that context, research into Supply Chain Design (SCD) has moved towards addressing the sustainability of businesses. Early sustainability approaches to the analysis and design of supply chains focused on environmental issues (Sellitto et al., 2019), but as time passed, new approaches have emerged. These have concentrated not only on the environmental aspects of supply chains but also on economic and social factors. A sustainable supply chain comes down to the integration of strategic, tactical, and operational activities with what is referred to as the Triple-Bottom-Line (TBL) objectives of sustainability, which is a combination of economic, environmental and social dimensions (Montoya-Torres, 2015). Therefore, it is essential to implement the optimal design of supply chains that not only lowers costs but includes environmental and social factors as well.

As illustrated by the impressive number of literature reviews published in the last few years, the number of publications addressing environmental and social assessments of the supply chain design problem has rapidly increased over the last several years. As highlighted in the review of the scientific literature (Barbosa-Póvoa et al., 2018; Beske et al., 2014; Dubey et al., 2017; Eskandarpour et al., 2015; Rajeev et al., 2017; Touboulic & Walker, 2015), there is a lack of societal factor evaluation into the design of sustainable supply chains. While it is expected that the three dimensions of sustainability work together into the assessment, previous studies usually deal with just one or two dimensions simultaneously. So, it is highlighted that the interrelation of the three dimensions is scarcely studied. Another finding of the analysis of literature, mainly relevant for the academic standpoint, is the need to develop conceptual models and frameworks and to propose measure indicators and metrics for the evaluation of sustainability into the supply chain management and design.

Finally, there is a need for developing theory–practice studies and empirical research for specific industrial sectors (Brandenburg et al., 2018; Fahimnia et al., 2017; Moreno-Camacho et al., 2019). This gap in sustainable supply chain design literature is sustained by the fact that the needs of sustainability and performance assessment of different industries are not quite identical. Sustainability in the food industry is an issue receiving increasing attention in the last few years since the growing population generates an enormous pressure in food supply (Rohmer et al., 2019). In many countries, especially in developing countries, the Agri-food sector plays an essential role in the economy by being a significant contributor to gross domestic product (GDP) and constitutes an essential agent in the economic, social and environmentally sustainable development of rural communities (Naik & Suresh, 2018).

The lack of societal factors and of case studies, the need of conceptual model, and metrics for sustainable evaluation are the main gaps identified in the literature review. Concerning these gaps, this paper proposes the analysis of different structures in the design of a supply chain when the three dimensions of sustainability are evaluated. This paper contributes also to the SDGs Zero Hunger (number 2), decent work and economic growth (number 8), responsible consumption and production (number 12), and climate action (number 13). To do so, a multi-objective optimization model is proposed, and a proper solution procedure is implemented.

Besides, generalized approaches for supply chain design are somehow difficult to validate for all types of supply chains. Besides, the Operations Research (OR) methods commonly used to address problems in supply chain design have often been criticized for their shortcomings in fieldwork (Stindt et al., 2016). General metrics struggle to represent the complexity of the situation, and the specific industries are under study generating a lack of holistic understanding and shortcomings in the abstraction and its consequent modeling of real-world problems. Hence, the usefulness of these works as a support for decision-making in real applications is often compromised. In line with the previous statements, this paper considers a Colombia dairy supply chain as the bridge has to be built through case studies. As pointed

out by Tordecilla-Madera et al. (2017), the Colombian dairy sector faces a series of challenges regarding its successful entry to the international market and consolidation within the internal market. The Colombian National Council for Economic Policy (CONPES) has introduced policies for improving this sector's competitiveness (CONPES, 2010), through CONPES document No. 3675 that is aimed at improving the Colombian dairy sector's competitiveness by developing strategies whose goal is to reduce production costs, increasing productivity, promoting collaborative schemes, and strengthening the sector's institutional administration. Such policy also sought to improve sanitary and safety measures for strengthening competitiveness, improving public health, and gaining access to national and international markets; analysis has thus been undertaken at each level in the production chain, including associations/cooperatives representing the production, storage, transportation, manufacturing, and commercialization sectors, as well as those entities responsible for inspecting production, overseeing and controlling the processes so involved, and the sale of milk and other dairy products.

To sum up, a multi-objective optimization model where the three dimensions of sustainability in the supply chain are evaluated is proposed in a Colombia dairy supply chain as a case study. This paper is organized as follows. An overview of the literature applied to the Sustainable Supply Chain Network Design (SSCND) in the dairy sector is presented in Sect. 2. Section 3 is dedicated to the description of the problem and the main assumptions in the context of the studied sector. The multi-objective model for sustainable dairy supply chain network design is developed in Sect. 4. Computational experiments are presented in Sect. 5, while a sensitivity analysis is proposed in Sect. 6. Finally, Sect. 7 presents managerial implications, and Sect. 8 some concluding remarks and future research directions.

## 2 Literature review

The dairy sector as part of the agricultural sector is one of the largest contributors to greenhouse gas emissions in developed countries, but particularly in developing countries where the low productivity threatens natural ecosystems due, for example, to increasing food demand. Social aspects inherent to the development of the sector are not minor details for developing countries, where about 30% of the employment come from agricultural sources. Despite the clear interference of the social and environmental dimensions in the development of the sector, there are few works addressing the design of supply chains in the sector considering sustainable criteria. Moreover, Jouzdani and Govindan (2021) highlight that the dairy sector is understudied and need to be explored. This research aims to answer that call.

Sustainable supply chain network design (SSCND) incorporates the evaluation of environmental and social factors, concerning supplier selection, facilities location, production processes, technological choices, and transportation. Some of the associated criteria may be classified in the following topics, use of resources, pollution, biodiversity threats, work conditions, human rights actions, compliance with child labor, gender equity, among others (Chardine-Baumann & Botta-Genoulaz, 2014). Although some environmental factors can be expressed in economic terms such as taxes over greenhouse gas (GHG) emissions (Zakeri et al., 2015), others environmental, and especially some social factors, are not easily represented through a cost function.

As a result, the definition of a sustainable supply chain network from the operational research perspective becomes a Multi-Objective Optimization Problem (MOOP), and the modeling approach also becomes difficult, involving tradeoffs between conflicting objectives

(Mota et al., 2018). In fact, as presented by Eskandarpour et al. (2015) and Moreno-Camacho et al. (2019) about three-quarters of the works addressing sustainable supply chain design is based on multi-objective approaches. Since the social dimension has received less attention, many of the works focus on bi-objective models considering economic and environmental performance assessment.

For instance, Rohmer et al. (2019) use a novel linear programming formulation with a multi-objective optimization (cost and environmental objectives). Their case study is based on life cycle analysis and consider food production and consumption decisions. They highlight the need of modeling the global supply chain and the importance of the choice of the indicators in a context of conflicting sustainable aspects. Dolgui et al. (2019) adds that problems with complex interrelations between process dynamics, capacity evolution, and dynamic setups require further investigation.

Although life cycle assessment methodologies have been described in the literature as the most reliable method currently available for assessing environmental impacts of a particular product or process, its application may not always be possible due to its complex and time-consuming process (Eskandarpour et al., 2015). Thus, some researchers choose to carry out a partial evaluation of environmental factors, focusing on which results are more challenging to the problem under study. Cuong et al. (2021) created for instance a three-stage production–distribution model. Accorsi et al. (2016) developed a linear programming model to the design of a zero-emission supply chain with an application in the potato farming context. The model considers a land-use assessment for the location of crops, processing facilities, warehouses, forests, and renewable energy production fields. Overall emissions associated with crops and logistics activities are compensated by the planting of forests and the use of renewable energies. In Escobar et al. (2017), an optimization model for the supply network for the fish industry is developed. The authors proposed a single objective model with a penalty cost associated with waste production at fishing farms. Miranda-Ackerman et al. (2017) presented a nonlinear multi-objective model for the green supply chain network design for orange juice. The environmental objective calculates the equivalent $CO_2$e emissions generated by the orchard production, pasteurization process, bottling, and transportation activities. The model considers organic and conventional farming and technology selection. Pricing strategies related to green consumer behavior are evaluated through different scenarios. The authors presented a Genetic Algorithm and Multicriteria Decision-Making tool to solve the model. Fang et al. (2018) addressed the design of a cold supply chain network for transportation of fresh Agri-products to China. Ngoc et al. (2021) study specifically the maritime transportation with the Lokta-Volterra equation. The environmental objective aims to minimize the amount of $CO_2$e emissions from transportation and DC's operations, while to the economic pillar they consider minimization of total costs.

However, some works consider the three pillars. Yakavenka et al. (2019) developed a multi-objective model in the case of perishable food products. They analyzed trade-offs between the three pillars of sustainability (cost, social time and emission). Anvari and Turkay (2017) recognized the inverse relation between environmental and social performance at the location of industrial facilities. Considering that the economic growth that boost social development is regularly performed at the expense of natural resources. For instance, the construction of a new production plant in a specific region might represent job opportunities for its inhabitants, but also promotes the immigration into the region, adding pressure on general community services such, hospital, schools and so on. In addition to the environmental impacts caused during both the construction and the operation phase of the facility, which might include among others, discharges of solid wastes, water flows pollution, and noise and air pollution. Jouzdani and Govindan (2021) propose a multi-objective mathematical programming model

applied in the dairy sector and study the three pillars of sustainability. They conclude that emphasizing the economic pillar has strong negative impacts on both environment and social pillars.

As stated by Eskandarpour et al. (2015), goal programming approach has received less attention addressing sustainable supply chain network design; Few examples on its application on the design of a supply chain as for a biofuel supply chain in Miret et al. (2016). The present research aims to bridge this gap, and reinforce the research including the three dimensions of sustainability.

Considering how and when preferences from decision makers are included into the solution procedure, four main approaches are considered in the literature, namely, no-preference, a priori, a posteriori, and interactive methods. Typically, a priori methods for the solution of multi-objective optimization model entails the definition of preferences of the decision maker prior to the modeling process. The preferences can be asked as a weights or relative importance of the objectives. Indeed, the weight sum method is one of the most common methods used to address SSCND. The weight sum method entails selecting a set of scalars weights to compose a unique objective function combining all the objectives in the problem. Afshari et al. (2016) presented a weighted sum method to the design of a closed-loop supply chain under uncertainty. They consider customer satisfaction and supply chain total cost as objectives to evaluate the social and economic dimensions, respectively. Colicchia et al. (2016) addressed the selection of transit points and the allocation of demand for a chocolate manufacturer, considering environmental impacts coming from transportation and warehousing activities. Wang et al. (2018) considered a bi-objective nonlinear programming model to the design of a supply chain, where different raw material might be selected, according to its purchase price, production cost and carbon emissions. Profit maximization and carbon emissions minimization are considered in a weighted sum method.

On the other hand, by using a posteriori method, a set of equally optimal solutions (Pareto optimal) is generated, and the decision maker may choose the one that suits the company objectives the best. Here, the most preferable method in the literature is the ε-constraint method. Varsei and Polyakovskiy (2017) developed a mixed-integer linear programming model in a large-sized wine company in Australia. The environmental objective calculates the $CO_2e$ emissions generated by transportation activities between facilities through the whole supply chain. To solve the model, they used an augmented ε-constraint method. For Kucukvar et al. (2019), the industry has the largest environmental footprints in food supply chains.

However, as stated by Hartikainen et al. (2011), several a priori methods could be utilized to construct a pareto optimal front by the solution of multiple single objective problems. For instance, Murillo-Alvarado et al. (2015) proposed an ε-constraint method to design a biorefinery supply chain based on residues of the tequila industry in Mexico. They considered simultaneously economic and environmental objectives. In the category of financial performance, the decided profits as an economic performance indicator, while the environmental impact associated with transportation and production activities within the network is calculated through the Eco-Indicator 99 method. Cambero et al. (2016) addressed the design of a bioenergy fuel supply chain considering economic as well as environmental impacts. Net present value (NPV) is used to calculate economic performance and the environmental objective aims to maximize the greenhouse emission savings with the introduction of a biorefinery supply chain, putting it differently to maximize the difference in the total amount of GHG emissions between a baseline scenario with no biorefinery and an alternative scenario where forest and wood residues are harnessed to the operation of a biorefinery to produce biofuels and energy. In the model, forest mill, biorefinery operation, biomass and biofuel

transportation, and energy generation are considered to calculate $CO_2$ equivalent emissions ($CO_2$e). They used an augmented ε-constraint method to solve the problem. Cambero and Sowlati (2016) used the same method and presented an extension of the biorefinery supply chain network design to consider social aspects. The social benefit is estimated as a weighted sum of the different social impacts of different types of jobs created in different locations. Previous works used the ε-constraint method to solve sustainable supply chain design in different sectors as wine industry (Varsei & Polyakovskiy, 2017), biofuels (Gargalo et al., 2017; Nodooshan et al., 2018; Osmani & Zhang, 2017; Rabbani et al., 2018), home appliances (Urata et al., 2017), and agri-products (Fang et al., 2018).

Other solution procedures include the method of weighted metrics, here the objective is to find the closest feasible solution to a reference point, which is usually the ideal point (i.e., a point where the multiple objectives reach its optimal value). This method was used in Zhang et al. (2016) for the robust design of a biodiesel supply chain based on waste cooking oil. Govindan et al. (2016) addressed the design of a closed-loop supply chain for the electrical manufacturing industry. The economic dimension is evaluated through the maximization of profits. The saved costs by the recovery activities and the cost of $CO_2$e emissions are accounted for the environmental dimension. Finally, the social pillar is represented by a weighted sum of social indicators, including economic welfare and growth, extended producer responsibility, and employment. The three-objective model is solved using the weighted metrics method. Asadi et al. (2018), proposed a bi-objective model for the design of a biofuel supply chain. In the model, the minimization of costs and impacts via $CO_2$e emission are considered to the performance in the economic and the environmental dimension, respectively. The authors compared the performance of Multi-Objective Particle Swarm Optimization (MOPSO) and the Non-Sorting Genetic Algorithm (NSGA-II) to solve this problem. In fact, evolutionary algorithms have gained attention in the SSCND context (Afshari et al., 2016; Miranda-Ackerman et al., 2017).

However, in the context of sustainability at supply chain level, there are some inherent inconveniences related to the application of a priori and a posteriori method. First, there is a difficulty of selecting the weights to cope with problems of scale, since the objectives have different magnitudes (monetary units, GHG emissions, Eco-points, lost days, jobs, and so on) (Ehrgott & Wiecek, 2005). Second, for a priori methods, it is expected from the decision maker to have some knowledge about the interdependencies of the objectives and the feasible objectives values (Hartikainen et al., 2011). However, sustainability encompasses a broad set of requirements, many of them outside of the focus of classic business decisions, and the expected results coming from the appropriation of sustainable practices might be difficult to estimate. Therefore, there is no certainty in the accurate selection of weights by the decision maker. Third, the visualization of the set of Pareto optimal solutions is not easy when the problem considers three or more objectives. Additionally, the selection of one option when a large set of solutions is displayed becomes a tough task even more when the trade-off between the conflicting objectives is not well understood (Khan et al., 2020). Moreover, considering the rise in the definition of national and continental plans to the reduction of GHG emissions and the improvement of social health and living conditions, it makes sense to establish expected values to the sustainability objectives considering information from outside the company. Lastly, the present research aims to define targets and analyze different scenarios for the trade-offs.

# 3 Problem statement

In developing countries, particularly, the dairy sector is characterized by a large number of smallholders in the production link and a reduced number of buyers in the processing level, resulting in a significant inequity in the sector. The low associativity of the farmers and the high variations of productivity in the cattle farms, due to the low technical level of exploitation, represent a great disadvantage in the negotiation for the small farmers.

Moreover, specifically in the Colombian case, there is a noticeable difference between production and processing capabilities. The industry is only capable of processing about 48% of the total milk produced on farms, which causes the appearance of informal collectors, who take advantage of the situation to pay producers below what is legally established per liter of raw milk. This situation exacerbates the problem of low wages in the sector and the inequality of development between urban and rural zones.

Having said that, the location and planning capacity of the distribution network carry out several major impacts regarding economy, environmental and society for dairy companies; serving urban markets, as well for milk producers, located in rural areas. Therefore, we address the problem of designing a regional dairy supply chain network considering objectives in the three dimensions of sustainability. The current section presents the description of the problem and the main assumption in the context of the case study. We consider the design of a single-period, four-tier supply chain, composed of production sites, processing plants, distribution centers, and retailers, as shown in Fig. 1. In the supply chain of the case study, processing plants receive raw milk coming directly from farms or from milk collection centers. These are hubs for the consolidation of milk coming from small dairy farms. Once at processing facilities, raw milk is pasteurized and homogenized to extend the shelf life of milk and to ensure product quality. Several dairy products are packaged, and some quality tests are applied before shipment approval. Although processed milk and other several dairy products such as yogurt, cream, cheese, and whey are produced and transported through the network, to simplify the mathematical formulation, we consider a single aggregated unit for the product going from farms to retailers (e.g., tons of milk). After the transformation process, several types of milk and dairy products are shipped from the processing plants to the different distribution centers (DC's). Finally, the products are sent to retailers to meet demand.

Hence, the model aims to determine the optimal location and capacity of processing and distribution facilities, to choose the suppliers from a set of potential candidates, to determine transportation modes between suppliers and plants, plants and distribution centers, distribution centers and retailers, and finally, to define the quantity of product that goes from one facility to another, in order to satisfy the demand of dairy products in a set of regions. Due to the unique characteristics of the product, no inventory is considered by the end of the period for raw milk nor for dairy products, at processing and distribution facilities. Decisions on the location of plants and distribution centers in the regions are guided by two types of costs.
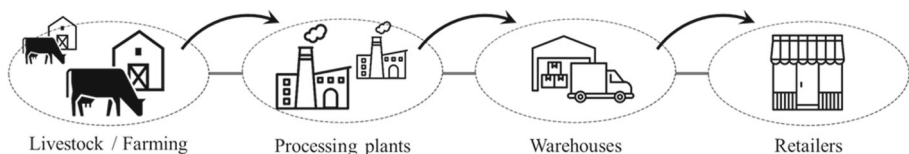


**Fig. 1** Structure of the dairy supply chain under study

Fixed costs, related to the capacity of the facility, are paid only if the corresponding facility is selected. Variable costs are related to the total volume of production at the corresponding facility. We consider three different capacity levels for.

In our study only road transportation is available. However, given the plurality of road conditions to access farms, distribution centers in small villages, or retailers in downtown, etc., different types of trucks are considered. It is assumed that a restricted set of suitable transportation modes has been identified a priori for each supplier and retailer, considering the road characteristics. For instance, due to road conditions, such as road width, freight weight restrictions and so on, some farms, collection centers or retailers might present restrictions to the use of certain types of trucks. The model considers three types of trucks, namely, light truck, medium truck, and heavy truck, all conditioned for the transport of refrigerated freight and differentiated by different load capacities and consumption of fuel. The transportation cost is assumed linear in function to the quantity carried and the covered distance to each type of truck. GHG emissions are calculated by multiplying the consumption of fuel by its corresponding emission factor. More in the assumptions of the model, we identify potential locations for the construction of processing locations and DC's. Moreover, we consider three different capacity alternatives for processing plants and DC's. While suppliers and retailers locations are predefined and definitive. Finally, demand in every region is known.

The supply chain configuration considers economic, environmental, and social factors. To evaluate the economic performance, the objective aims to minimize the total network costs, including facilities location costs, procurement costs, processing costs, and transportation costs. The environmental dimension is evaluated through the quantification of $CO_2e$ emissions coming from production and transportation activities. Environmental impact of livestock activities and its related problems are not included. Finally, the social objective is to maximize the social impact caused by the creation of employees at processing facilities and the purchase of milk from local farms. Priority has been given to less developed regions both, for the selection of suppliers and the installation of processing plants.

## 4 Mathematical formulation

We formulate the problem as a mixed-integer programming model as follows. We define a set of suppliers S, including both farmers (F) and collecting centers (C), let $S = F \cup C$. We also define a set of potential locations to install processing plants P, a set of potential zones to locate distribution centers D, a set of retailers R, a set of available transportation types, from farmers to processing plants M and from processing plants to distribution centers and retailers T. Moreover, Finally, CP and CD are the sets containing capacity options for processing plants P and distribution centers D, respectively. We define the following decision variables and parameters.

### 4.1 Decision variables

- $x_{spm}$: quantity of litters of raw milk shipped from supplier $s \in$ S to processing plant $p \in$ P delivered in vehicle type $m \in$ M
- $x_{pdt}$: quantity of aggregated units of processing milk delivered from processing plant $p \in$ P to distribution center $d \in$ D by vehicle type $t \in$ T
- $x_{drt}$: quantity of aggregated units of processing milk sent from distribution center $d \in$ D to retailer $r \in$ R by vehicle type $t \in$ T

- $y_s$: equal to 1 if supplier $s \in$ S supplies any quantity of raw milk to processing plants or collecting centers, 0 otherwise
- $y_{pcp}$: equal to 1 if a processing plant is in potential zone $p \in$ P with capacity $cp \in$ CP
- $y_{dcd}$: equal to 1 if a distribution center is open in potential zone $cd \in$ CD with capacity $cd \in$ CD

## 4.2 Parameters

We distinguish parameters in three different aspects: location, production, and transportation costs in the economic dimension.

- $LC_{cp}$: fixed cost of opening a processing plant with capacity $cp \in$ CP
- $LC_{cd}$: fixed cost of opening a distribution center with capacity $cd \in$ CD
- $Pr_s$: Price of raw milk per ton at supplier $s \in$ S
- $PC$: processing cost per aggregated unit at processing plants
- $Dist1_{sp}$: Distance in km between the supplier $s \in$ S and the processing plant $p \in$ P
- $Dist2_{pd}$: Distance in km between the processing plant $p \in$ P and the distribution center $d \in$ D
- $Dist3_{dr}$: Distance in km between the supplier $d \in$ D and the retailer $r \in$ R
- $TC_t$: transportation cost per ton of milk in transport $t \in$ T
- $CS_s$: maximum supply capacity of supplier $s \in$ S
- $CM_{cp}$: production capacity of a processing plant with capacity $cp \in$ CP
- $Mop$: maximum desired occupation rate of processing facilities
- $Mup$: minimum allowed operation rate for processing facilities
- $CDC_{cd}$: storage capacity at distribution center with capacity $cd \in$ CD
- $Mudc$: minimum allowed operation rate for processing facilities
- $Dem_r$: Demand of retailer $r \in$ R
- $Trv_{sm}$: equal to 1 if vehicle type $m \in$ M have access to retailer $s \in$ S
- $Trv_{rt}$: equal to 1 if transport type $t \in$ T have access to retailer $r \in$ R
- $Fcons_m$: Fuel efficiency of vehicle type $m \in$ M kilometers per gallon
- $Fcons_t$: Fuel efficiency of vehicle type $t \in$ T kilometers per gallon
- $Cap_m$: Capacity in tons of milk of vehicle type $m \in$ M
- $Cap_t$: Capacity in tons of milk of vehicle type $t \in$ T

  We use the following notation in referring to the environmental factors of the model.

- $Emfc$: $CO_2$e emission produced per consumed gallon of fuel
- $Empr$: $CO_2$e emissions produced per ton of milk processed at the plant

  Additionally, we use the following parameters evaluating the social performance in the social dimension.

- $Jo_{cp}$: jobs opportunities created by locating a processing facility with capacity $cp \in$ CP
- $Ur_p$: Unemployment rate at the potential location of processing plant $p \in$ P
- $\varphi_s$: Added value factor of the region of supplier $s \in$ S

## 4.3 Objective functions

Assessment of impacts in social and environmental and economic dimensions are included as separate objectives in the model. The first objective function (1) aims to the minimization

of the total cost ($Z_1$). This cost is the sum of opening facilities cost (i.e., processing plants and distribution centers), purchasing cost, production cost at processing plants and cost of transportation from processing plants and nodes downstream in the chain.

$$Z_1 = \sum_{p \in P, cp \in CP} LC_{cp} * y_{pcp} + \sum_{d \in D, cd \in CD} LC_{cd} * y_{dcd} + \sum_{s \in S, p \in P, m \in M} Pr_s * x_{spm}$$
$$+ \sum_{p \in P, d \in D, t \in T} PC * x_{pdt} + \sum_{p \in P, d \in D, t \in T} TC_t * x_{pdt}$$
$$+ \sum_{d \in D, r \in R, t \in T} TC_t * x_{drt} \tag{1}$$

The objective at the environmental dimension ($Z_2$) focuses on the pollution caused by the production process and transportation. Equation (2) calculates $CO_2$e emissions emitted from transportation activities at the different tiers and the emissions coming from the processing production of raw milk.

$$Z_2 = \sum_{s \in S, p \in P, m \in M} \frac{Emfc * Dist1_{sp} * x_{spm}}{Cap_m * Fcons_m} + \sum_{p \in P, s \in S, t \in T} \frac{Emfc * Dist2_{pd} * x_{pdt}}{Cap_t * Fcons_t}$$
$$+ \sum_{p \in P, s \in S, t \in T} \frac{Emfc * Dist3_{dr} * x_{drt}}{Cap_t * Fcons_t} + \sum_{p \in P, d \in D, t \in T} Empr * x_{pdt} \tag{2}$$

Two different factors represent the social objective of the developed model. The first one, to maximize the social benefit associated with the generation of employment in the zone of located processing plants. The second one, to maximize the social benefit associated with the selection of a farmer as a supplier. These two objectives are evaluated together in a normalized Eq. (3). The denominator of each term in the equation is a sum of parameters representing the maximum possible value to obtain. For instance, $\sum_{s \in S} \varphi_s$, corresponds to the sum of add value factor for all regions of suppliers $s \in$ So each term in (3) becomes in a percentage respect to an upper bound of it self.

$$Z_3 = \frac{\sum_{p \in P, cp \in CP} Ur_p * y_{pcp}}{\sum_{p \in P} Ur_p} + \frac{\sum_{s \in S} \varphi_s * y_s}{\sum_{s \in S} \varphi_s} \tag{3}$$

## 4.4 Model formulation

This section presents the equations of the generic model.

### 4.4.1 Demand and flow conservation constraints

$$\sum_{d \in D, t \in T} x_{drt} = Dem_r \quad r \in R \tag{4}$$

$$\sum_{s \in S, m \in M} x_{spm} = \sum_{d \in D, t \in T} x_{pdt} \quad p \in P \tag{5}$$

$$\sum_{r \in R, t \in T} x_{drt} = \sum_{p \in P, t \in T} x_{pdt} \quad d \in D \tag{6}$$

Equation (4) ensures that the retailer's demand is met. Equations (5) and (6) guarantee the flow balance at processing plants and distribution centers, respectively, by equating the total

inputs and outputs at each type of facility. To avoid unrealistic results when considering the social dimension, Eqs. (4), (5) and (6) are defined as equalities. As an example, if demand is not established as an equality, the model in the third scenario could lead to an overflow of production seeking to create a large number of employees, resulting in an unrealistic operation.

### 4.4.2 Facilities capacity constraints

$$\sum_{p \in P, m \in M} x_{spm} \leq CS_s * y_s \quad s \in S \tag{7}$$

$$\sum_{d \in D, t \in T} x_{pdt} \leq \sum_{cp \in CP} CM_{cp} * y_{pcp} * Mop \quad p \in P \tag{8}$$

$$\sum_{p \in P, t \in T} x_{pdt} \leq \sum_{j \in J} CDC_{cd} * y_{dcp} \quad d \in D \tag{9}$$

Constraint (7) limits the total amount of raw milk shipped from supplier $s \in S$ to processing plants $p \in P$ to the capacity of each supplier. Constraint (8) establishes bounds for the quantity of production at each opened processing plant. Constraint (9) ensures that the capacity of the distribution center is not exceeded.

*Transport availability*

$$\sum_{p \in P} x_{spm} \leq CS_s * Trv_{sm} \quad s \in S, m \in M \tag{10}$$

$$\sum_{d \in D} x_{drt} \leq \sum_{d \in D, cd \in CD} CDC_{cd} * y_{dcd} * Trv_{rt} \quad r \in R, t \in T \tag{11}$$

Constraints (10) and (11) ensures the delivery of raw milk and processed products only in available vehicles according to the restriction of access for each supplier and retailer, respectively.

### 4.4.3 Operational constraints

Addressing environmental and social assessment without operational conditions would drive into not realistic solutions (Brandenburg, 2015). Moreover, one of the critical factors in the social field of corporations is to be profitable; a profitable company is able to offer stable working conditions, contributes to the development of the region while satisfying the demand in the market. Hence, this model considers some minimal operational requirements expressed in the following constraints.

To avoid the creation of employees on idle processing plants, constraint (12) ensures that an open processing plant is used at least 50% of its capacity. In the dairy sector processing plants used to be constructed with a recognized overcapacity to attend fluctuations in the processing of raw milk in rainy months. Use of a plant at half its capacity might be acceptable. Constraint (13) imposes a minimum use of the capacity for open distribution centers. Constraints (14) and (15) limit to one the number of processing plants or distribution centers open at each selected region, respectively.

$$\sum_{d \in D, t \in T} x_{pdt} \geq \sum_{cp \in CP} CM_{cp} * y_{pcp} * Mup \quad p \in P \tag{12}$$

$$\sum_{p \in P, t \in T} x_{pdt} \geq \sum_{cd \in CD} CDC_{cd} * y_{dcd} * Mudc \quad d \in D \tag{13}$$

$$\sum_{cp \in CP} y_{pcp} \leq 1 \quad p \in P \tag{14}$$

$$\sum_{cd \in CD} y_{dcd} \leq 1 \quad d \in D \tag{15}$$

## 4.5 Solution approach

For the solution of the multi-objective optimization problem (MOOP) defined in the previous subsection, a Chebyshev goal programming is proposed to find a balance between the accomplishment of the objectives. Major goal programming formulations includes lexicographic, weighted and Chebyshev goal programming (Jones & Tamiz, 2010). Unlike lexicographic and weighted formulations where preferential weights are assigned to the set of unwanted deviation variables are assigned, Chebyshev GP aim to minimize the maximum deviation of every objective. To put differently, instead of minimizing the sum of all deviations, the approach focus on minimizing the maximal deviation of any goal (Jones & Tamiz, 2010). Chebyshev GP belongs to the category of *non-preference* solution methods. Unlike the other major formulations where the intervention of the decision-maker has a high influence on the final solution, by defining preferences over conflicting objectives. The Chebyshev goal programming aims to establish a good balance between the accomplishment of multiple goals.

In the context of sustainability assessment, it is not desirable to establish preferences on dimensions of sustainability. The deliberate prioritization of objectives and the use of weights might lead to choose variables values which together reach lowest function values, at the expense of a very poor performance in one or two of the goals. Hence, the solution method here employed aims to minimize the maximum undesirable deviations from the best possible performance of the supply chain at every assessed dimension (i.e., economic, environmental, and social). The main purpose of the solution approach is to identify the highest potential improvements achieved by the supply chain structure, while considering no bias or preferences among the objectives.

As part of the solution approach, a set of single objective optimization problems are solved to compute the best and worst possible values for each objective in the three dimensions of sustainability (i.e., economic, environmental, social). Hence, an ideal vector is constructed with the results of the individual optimization problems (Chiandussi et al., 2012). Let $f_{eco}^*$, $f_{env}^*$, $f_{soc}^*$ denote the optimum values for the three objectives. Hence the vector $f^* = [f_{eco}^*, f_{env}^*, f_{soc}^*]$, contains the ideal solution for the multi-objective problem. These results present the best possible performance of the supply chain at economic, environmental, and social dimension. The best values are then used as the upper bounds or the aspiration levels for the objectives. The objective becomes one, minimizing the differences from those aspirational levels, so the solution obtained minimizes the worst unwanted deviation from any single goal (Ghufran et al., 2015). To apply the goal programming approach to the solution of the MOOP, a new set of constraints need to be added (16). Let O be the value of an element of the set of the multiple objectives to be evaluated, $O \in \{Z1, Z2, Z3\}$, and let $n_O$ and $p_O$ be the negative and positive deviation of the objective O from its target value $O_{target}$, then:

$$O + n_o - p_o = O_{target} \forall O \in \{Z1, Z2, Z3\} \tag{16}$$

The Chebyshev goal programming aims to minimize the maximum undesirable deviations from the defined target for every single objective. In our specific case, since both economic and environmental objectives correspond to minimization functions, positive variations are undesirable for these objectives. Meanwhile, negative deviation is undesirable for the social objective, since the original objective is to maximize social impact. Let $Z1_{target}, Z2_{target}, Z3_{target}$ be the ideal values for the economic, environmental, and social values, respectively, and let $p_{Z1}$, $p_{Z2}$ and $n_{Z3}$ the undesirable deviations for each objective. For instance, as a rise in the total cost is an undesirable result to the economic dimension the positive deviation appears in the relation. While appears in the equation related to the social objective since here a negative deviation represents a low social impact. Finally, let $\lambda$ be a scalar representing the percentage deviation of each objective to the intended solution. Therefore, constraints (17)–(19) are added to the model, and (20) becomes the new objective function to be addressed.

$$\frac{p_{Z1}}{Z1_{target}} \leq \lambda \tag{17}$$

$$\frac{p_{Z2}}{Z2_{target}} \leq \lambda \tag{18}$$

$$\frac{n_{Z3}}{Z3_{target}} \leq \lambda \tag{19}$$

$$min \lambda \tag{20}$$

## 5 Computational experiments

### 5.1 Data gathering

The case described in this section is based on a realistic supply chain aiming to serve the demand for milk and milk-derived products in the central region of Colombia. Economic, environmental, and social data for the case study were obtained through sectoral entities, previous studies from governmental agencies, and sustainable reports of milk processing industries when possible. Sources used to obtain the data are listed in Table 1.

Table 1 Input parameters sources

| Input data | Sources |
|---|---|
| Procurement cost | DANE (2019) |
| Transportation cost from supplier to manufacturers | MADR (2018) |
| Transportation costs different tipe of trucks for distribution activities | SICETAC (MinTransporte, 2016) |
| Unemployment rate by location | Observatorio Sabana Centro (2019) |
| Average $CO_2$ emissions per ton of processed product | Alpina (2018) |
| Average $CO_2$ emissions per gallon of fuel | UPME (2016) |

Regarding investment cost for the construction of new facilities, production plants or warehouses, it is estimated by considering the price of similar facilities that are already built. The milk processing plant in Santa Marta (Colombia) with a capacity 20 million liters/year and an investment of USD $4.8 million in 2015 and the plant in Arauca that process about 11 million liter/year and its cost was USD $2.63 million in 2020. For warehouses, the investment is based on distribution centers owned by milk processing companies: 12,000 square meters with an investment of about USD $ 11 million in, 2016. Values are presented at the average Colombian COP exchange rate of USD in 2018. Likewise, the number of job opportunities created in processing stage is calculated with the number of direct jobs created in already established manufacturing plants.

As presented in Table 1 Environmental data for calculating impact caused by both, milk transportation and milk processing were obtained through a specific calculation tool for Colombian fuels and the revision of sustainability reports of dairy processing plants, respectively. Regarding the production process, both, scope one direct emissions for fuel combustion and fugitive emissions and scope two indirect emissions for purchasing electricity, heat, and steam are included. Finally, Colombian national statistics were considered to get data in the social dimension, unemployment rate and the percentage share of each municipality in the national GDP served as factors for the classification of the zones in more or less developed areas.

The model considers a regional supply chain for the distribution of dairy products in the central region of Colombia. Like most of the agri-food supply chain, production of raw material occurs in rural areas, while consumption centers are mainly located in urban areas in the big cities. The model considers the existence of 29 supplier along the region and 59 retailers points. The latter are mainly located in the capital city, while the former are present in the rural areas, in small towns around the capital city. The model considers the definition of the location of manufacturing plants and distribution centers to satisfy the demand in the aforementioned retailers. Particularly, it considers 4 alternative locations for manufacturing plants and 5 alternative locations for distribution centers as presented in Fig. 2.



**Fig. 2** Alternative locations for processing plants and distribution centers in the regional supply chain under study
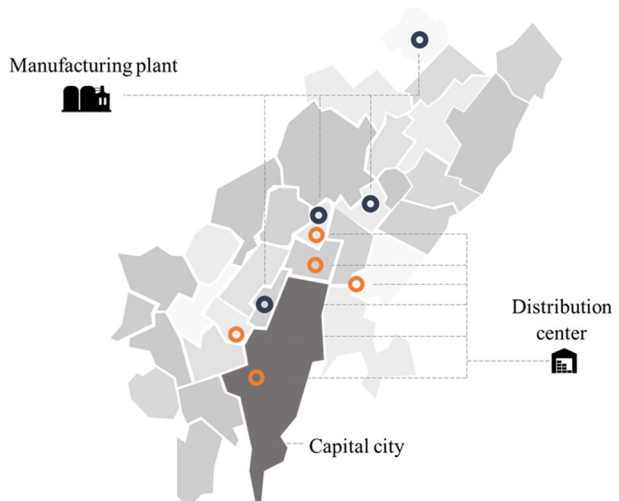
## 5.2 Definition of target levels

One of the key factors of goal programming is the definition of the set of target values for the involved objectives. To define the target of each one of the objectives, three separated linear programming models were executed without regard to the other two objectives. We use GAMS (General Algebraic Modeling Systems) with the MIP solver ILOG CPLEX 12.2. The experiments were conducted on a PC with processor Intel Core i5 4200U, 1.60 GHz and 8.00 GB of RAM. The computational time for the problem is negligible, and therefore, no analysis will be done in this regard. Results from these experiments are shown in Table 1. The first column of the table shows the three different objectives to be evaluated that correspond to Eqs. (1), (2), and (3), respectively. In front of each one of them, columns 2, 3, and 4 present the respective associated value for the remaining sustainability dimensions. The second column shows the total cost of the configuration in thousands of millions of Colombian pesos. The total emissions in tons of carbon are presented in column 3. The fourth column of the table presents the results for the social dimension, the objective function value (i.e., social impact factor) as well as the number of created jobs and the number of contracted suppliers in each configuration.

From Table 2, it is worthy to note the trade-offs between the different objectives. Slightly variations are presented in each one of the single objective scenarios analyzed. The network configuration aiming to minimize the total amount of $CO_2e$ emissions is about 7% more expensive than the best option and presents a reduction of only 3% in the $CO_2e$ emissions level. The difference in these costs is mainly caused by the number of distribution centers in each network structure. Although only one milk processing plant is open in each one of the different models, the model focuses on cost minimization accounts with two distribution centers of large capacity in zone 1 and zone 6, meanwhile the model with the environmental objective consists of four facilities at this level, two small capacity distribution centers in zones 4 and 6, one medium capacity distribution center in zone 1 and one distribution center of large capacity in zone 3.

Figure 3 presents a distribution of the drivers of cost for each one of the independent single-objective optimization problems. Production cost remains the same in every configuration. Small differences are observed in the procurement cost and transportation cost, while the cost

**Table 2** Results for single objective linear programming models

| Optimization function | Value of sustainability performance indicators | | | |
|---|---|---|---|---|
| | Total cost (COP '000M) | $CO_2$ emissions (Ton) | Social | |
| | | | Jobs | Suppliers |
| Economic objective (1) | **276.8*** | 45,395 | 1.102 | |
| | | | 130 | 20 |
| Environmental objective (2) | 298.4 | **44,347*** | 0.778 | |
| | | | 130 | 22 |
| Social objective (3) | 302.0 | 46,879 | **1.326*** | |
| | | | 130 | 29 |

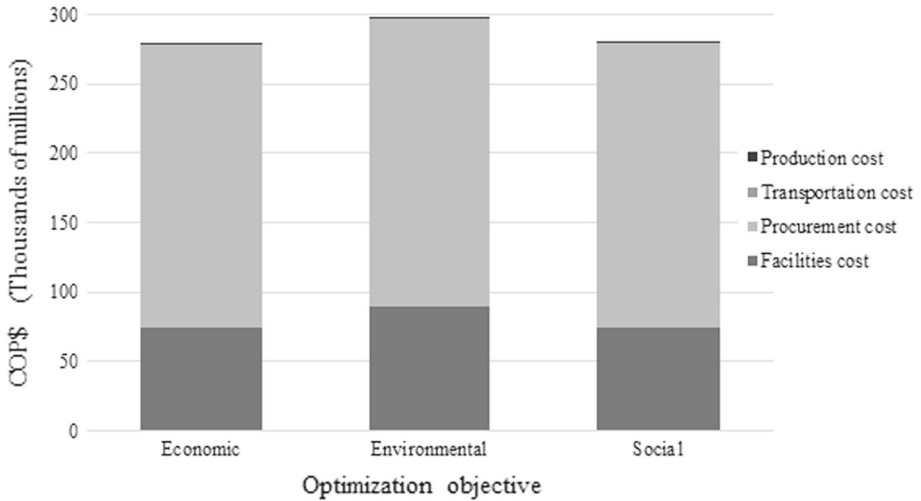*Bold numbers are the defined target for each objective

**Fig. 3** Drivers of cost for each model

of locations of facilities presents the most notable difference, particularly, to the reduction of GHG emissions.

It is also noted that the cost for the configuration guided by the social objective is very similar to the optimal one, in fact, it is just above 0.3% greater, but the level of $CO_2$e emissions is the highest among the evaluated possibilities. In fact, even when transportation costs in the scenario guided by the social objective increase just about 8% in comparison with the scenario guided by the environmental function, the level of emissions grows about 84%. Figure 4 presents a comparison in the level of $CO_2$e emissions generated by transportation activities between suppliers and plants, plants and DC's and DC's and retailers for the three
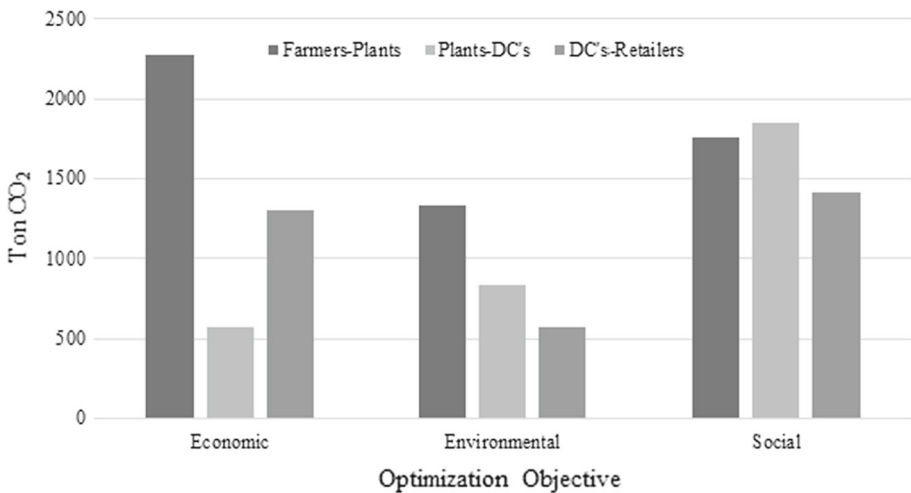


**Fig. 4** $CO_2$e emissions for transportation activities at different tiers

different single objective problems. The first scenario favors the location of a smaller number of processing plants, which increases the total number of kilometers traveled from farms to processing facilities, which is reflected in the notable contribution to the $CO_2$e emissions in this link. Conversely, the opening of more processing plants favors the reduction of emissions from transportation in the second scenario.

In the third scenario guided by the social objective, the number of tons of $CO_2$e derived from transportation activities increases considerably, mainly due to the transport of products between the production plant and the distribution centers. The reason is that in this scenario the decision regarding the location of processing plants and the selection of suppliers privileges the areas with the least development and the highest unemployment rate, which usually corresponds to those areas remote from large consumption centers and challenging access routes.

On the other hand, as also shown in Table 2, for all network configurations, the number of created jobs is the same: a processing plant of small capacity that requires 130 new employees.

Interestingly, although the optimization of the social dimension has negative impacts on the environmental performance measure as described before regarding the number of emissions, this does not occur in the other way around. In fact, the scenario guided by the environmental objective has a higher number of suppliers and reaches a social impact measure about 20% under the optimal. The main difference affecting the result on the social value indicator is the region in which the milk processing plant is installed and the region of the selected suppliers. While in the first case (i.e., environmental objective model) they are selected according to the minimum travel distance and the availability of use greener transportation means to cause the least amount of emissions, in the second case (i.e., social performance objective) they are selected prioritizing the areas with the least economic development. So, although the number of suppliers is higher in the scenario optimizing the environmental impact, the distribution of selected suppliers in the social scenario presents better performance.

Table 3 presents a summary of the results specifying the number of suppliers by zone and selected location for opening processing plant and distribution centers. To avoid a more massive extension of the table suppliers are divided into three different categories according to its value-added parameter ($\varphi_i$). Let F1 be the set of suppliers with the lowest values, $F1 = \{s_i | 0.1 \leq \varphi_i \leq 0.8\}, F2 = \{s_i | 0.8 < \varphi_i \leq 1.5\}$, finally, suppliers located in regions with the highest value are grouped in set 3 $F3 = \{s_i | \varphi_i \geq 1.5\}$. Moreover, potential facility locations for processing plants are listed from P1 to P4, being P1 the potential location with the highest unemployment rate, P2 the second and so on. The first column of Table 3 presents the objective function evaluated in the model. Columns two, three and four, present the number of suppliers at each category, Then, in column five to eight the potential location for processing facilities. We use the letter S from small, M from medium and L from large to present the capacity

**Table 3** Summary of the network structure for each independent model

| Objective function | Suppliers | | | Processing plants | | | | Distribution centers | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | F1 | F2 | F3 | P1 | P2 | P3 | P4 | C1 | C2 | C3 | C4 | C5 | C6 |
| Z1 | 14 | 2 | 3 | | | S | | L | | | | | L |
| Z2 | 13 | 6 | 5 | | | | S | M | | L | S | | S |
| Z3 | 17 | 4 | 2 | S | | | | L | L | | | | |

of the processing plant at the selected location. The same convention is used to describe the capacity of installed distribution centers in the six potential locations.

## 5.3 Chebyshev goal programming

Due to slight variations in different configurations of the supply chain, a non-weighted Chebyshev goal programming is used to balance the economic, environmental, and social objective in the problem under study. After defining, the target $Z1*$, $Z2*$ and $Z3*$ from the optimization of individual objectives in Sect. 5.2, the Chebyshev goal programming is performed as described in Sect. 4.5. From the execution is possible to note that there does not exist a configuration in which all objective targets are met without deviation. So, different trade-offs are presented in the new structure of the supply chain. Results of the execution are shown in Table 4. The first and second column present the objective and its related target, in the third column is presented the deviation respect to the target value with a plus sign (+) if it corresponds to a positive deviation or minus sign (−) if it corresponds to a negative deviation. Finally, the last column presents the percentage of variation for each objective and the value of lambda in bold.

Variations are presented for all objectives—the largest of these regarding the environmental issue. The new structure of the supply network has an increase of about 4% in the level of $CO_2e$ emissions above the desired value for this objective. Is worthy to note how this value is higher than the emission caused in the scenario guided by the economic function and allows us to see the complexity of the relationship between environmental and social objectives. In fact, this solution prioritizes the social performance of the supply chain. Regarding the structure, 16 suppliers from the least developed regions are selected, and the processing plant is also installed in the region with the highest unemployment rate. Three distribution centers are open: one small capacity distribution center in zone 4, one medium capacity distribution center in zone 2 and on a large capacity distribution center in zone 6. Summary of the structure of the network given by goal programming is presented in Table 5.

It is possible to observe how a reduction of emissions of $CO_2e$ requires an economic effort. Moreover, we highlight the relation between environmental and social performances;

**Table 4** Results of Chebyshev goal programming

| Objective | Target | Calculated deviation | λ |
|---|---|---|---|
| Z1 | 2.768E+11 | (+) 1.01E+10 | 3.69 |
| Z2 | 44,347 | (+) 1,780.55 | **3.69** |
| Z3 | 1.32 | (−) 0.044 | 3.62 |

Bold numbers are the defined target for each objective

**Table 5** Structure of the supply chain Chebyshev goal programming

| Objective function | Suppliers | | | Processing plants | | | | Distribution Centers | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | F1 | F2 | F3 | P1 | P2 | P3 | P4 | C1 | C2 | C3 | C4 | C5 | C6 |
| GP | 16 | 1 | 3 | S | | | | | M | | S | | L |

the pursuit of better results in social performance ends up affecting the environmental performance of the distribution network. One of the significant factors is the unavailability of efficient roads to transport products from isolated regions.

Herein lies the relevance of defining objectives to the sustainable key indicators. The definition of preferences by the decision maker can lead to good solutions, however, even when these solutions mean an improvement over the current company situation, in a broader view, might remain unsustainable in reference to the social and environmental objectives of the sector or the country.

## 6 Sensitivity analysis

When analyzing the characteristics and behavior of the system under study, it is important to highlight that various parameters in the model are subject to uncertainty. To deal with this, and to aid decision makers, this section presents the results of a sensitivity analysis.

### 6.1 Sensitivity analysis of parameter of facilities location cost

In this section, we evaluate the changes on the supply chain structure derived from variations in cost facility installation. It includes the installation cost of manufacturing plants and distribution centers. Table 6 presents the results of the Chebyshev goal programming for different variation on facility cost. Each row presents the actual value for each objective and the corresponding percentage deviation from the desired target when consider a defined variation on location facility cost.

The results show slightly variations within the interval 20% reduction to 10% increase. In this interval percentual variations are almost the same to each objective around 4%. In fact, results indicate that reduction in total cost are only about 1% in comparison with the initial

**Table 6** Results of the goal programming model to variations on location facility cost

| Facility location cost | $\lambda$ | Percentage deviation | | | Jobs | Suppliers |
|---|---|---|---|---|---|---|
| | | Economic goal | Environmental goal | Social goal | | |
| 30% Increase | 0.0818 | 3.00E+11 | 47,797.413 | 1.241 | 130 | 21 |
| | | 8.29% | 7.78% | 6.41% | | |
| 20% Increase | 0.0549 | 2.92E+11 | 46,617.21 | 1.254 | 130 | 22 |
| | | 5.48% | 5.12% | 5.43% | | |
| 10% Increase | 0.0369 | 2.87E+11 | 45,987.027 | 1.278 | 130 | 25 |
| | | 3.70% | 3.70% | 3.62% | | |
| Initial scenario | 0.0369 | 2.87E+11 | 45,983.624 | 1.278 | 130 | 26 |
| | | 3.69% | 3.69% | 3.62% | | |
| 10% Reduction | 0.0361 | 2.87E+11 | 45,949.848 | 1.278 | 130 | 27 |
| | | 3.61% | 3.61% | 3.62% | | |
| 20% Reduction | 0.0378 | 2.87E+11 | 46,023.493 | 1.278 | 130 | 25 |
| | | 3.78% | 3.78% | 3.62% | | |

scenario. This is evidenced by the slight variation on the value of $\lambda$ in the goal programming model. On the other hand, increasing facility location cost above 20%, implies a rise as well in $CO_2$ emission and a decrement in social performance. As presented in Table 1 the number of suppliers comes down when the facility cost increase. Moreover, the solution prompt to reduce the total number of distributions and prioritize the construction of facilities with higher capacities. It implies a growth in transportation activities which has a direct impact on the amount of $CO_2$ emissions.

Figure 5 presents the structure of the optimal configuration for the regional supply chain considering variations on facility location costs. Associated to each configuration we present a bar representing the transportation costs. The results show that, the higher the facility location cost the fewer distribution centers are located. With a reduction of 20% on the facility location costs solution goes for the construction of four distribution center with the lowest capacity (Fig. 5b). As the location cost increases the solution prioritizes the construction of distribution center with higher capacity, taking advantage of economies of scale. For instance, with a 30%
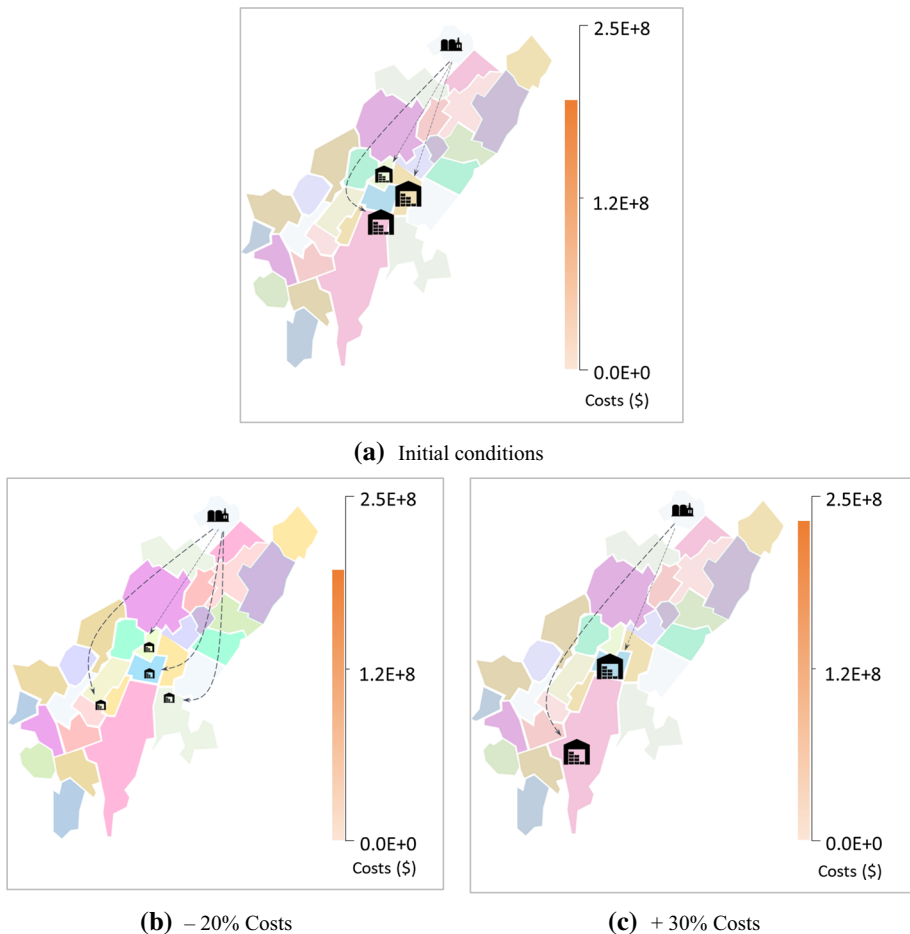


(a) Initial conditions

(b) − 20% Costs

(c) + 30% Costs

**Fig. 5** Effects of the facility location cost variation on the supply chain structure. **a** Initial conditions. **b** 20% Reduction facility cost. **c** 30% Increase facility cost

**Table 7** Percentual variation of the objective to different demand levels

| Demand | λ | Percentage deviation | | | Jobs | Suppliers |
|---|---|---|---|---|---|---|
| | | Economic goal | Environmental goal | Social goal | | |
| 30% Increase | 0.316 | 3.65E+11 | 58,384.338 | 1.184 | 320 | 27 |
| | | 31.65% | 31.65% | 10.71% | | |
| 20% Increase | 0.230 | 3.41E+11 | 54,509.51 | 1.17 | 320 | 24 |
| | | 23.09% | 22.92% | 11.76% | | |
| 10% Increase | 0.107 | 3.07E+11 | 49,134.046 | 1.184 | 130 | 26 |
| | | 10.79% | 10.79% | 10.71% | | |
| Initial scenario | 0.036 | 2.87E+11 | 45,983.624 | 1.278 | 130 | 26 |
| | | 3.69% | 3.69% | 3.62% | | |
| 10% Reduction | 0.0001 | 2.72E+11 | 43,382.141 | 1.326 | 130 | 29 |
| | | − 1.59% | − 2.18% | 0.00% | | |
| 20% Reduction | 0.0001 | 2.46E+11 | 38,445.592 | 1.326 | 130 | 29 |
| | | − 11.14% | − 13.31% | 0.00% | | |
| 30% Reduction | 0.044 | 2.23E+11 | 32,449.832 | 1.267 | 130 | 29 |
| | | − 19.37% | − 26.83% | 4.45% | | |

increase the solution consider the construction of just two distribution centers with the highest considered capacity. However, with fewer distribution centers transportation cost increase as shown in Fig. 5c and so does $CO_2$ emissions as it was mentioned above.

## 6.2 Sensitivity analysis of parameter of demand

The results of the goal programming model for different variations in the demand parameter are discussed below. Table 7 presents the actual value and the percentual variations for each objective to the established target. It is possible to appreciate a direct relation between demand and total costs as well as between demand and $CO_2$ emissions.

Figure 6 presents the behavior of the percentual deviation for the different objectives to different demand levels. We can observe how the total cost and the $CO_2$ emissions increase as the demand grow. The behavior of the social objective seems to have a different behavior. Although greater demand involves a larger number of job employees, the social performance does not seem to improve as the demands grow. The reason is mainly because with a greater demand the model prioritizes solution in which the manufacturing plant is located near to the consumption areas. Since the social performance considers job opportunities in relation with redundancy in locations, and urban locations tends to present lower unemployment rate, the social performance does not boost directly with demand growth.

The sensitivity analysis shows how economic and environmental performance are the issues requiring more control since they usually establish a limit for the improvement on the sustainable development of the supply chain. Moreover, it shows the limitation of the supply chain within its current conditions. Additional alternatives must be considered to reach challenging objectives at environmental and social level. For instance, low level emission production alternatives or using low-emissions vehicles for distribution activities.
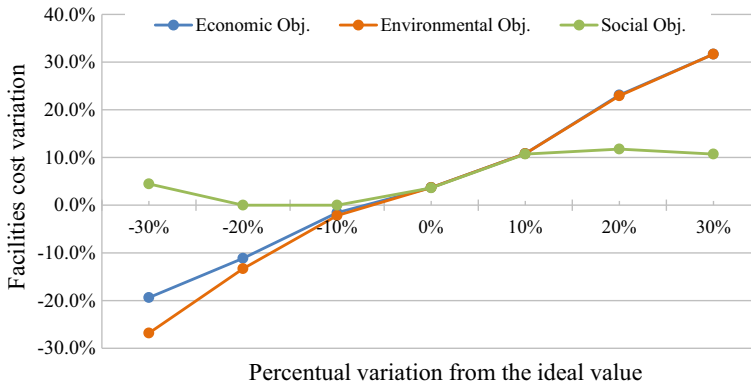
**Fig. 6** Effects of demand variation on percentual deviation by objective

# 7 Managerial implications

In today's globalized economies, as product technology becomes a commodity and the importance of service increases, it becomes more difficult for companies to compete through product differentiation, so many companies try to achieve competitive advantage through service to customers and clients. A company should not always rely on tangible aspects of the product to generate added value, but this can also be increased through better service. In this way, logistics becomes a source of competitive advantage to the extent that it manages to optimize the flow and cost of materials and products and offers adequate levels of service and reliability. Indeed, the design and management of supply chains has become a source of competitive advantages for virtually any service or manufacturing companies.

A fully sustainable supply chain is one that ensures socially responsible business practices, including the evaluation of environmental impact without forgetting the economic and productive performance. These practices are not only good for the planet and people who live here, but they also support business growth. These allow the companies in the supply chain to reduced environmental impacts, improve business continuity, gain on business reputation for potential for new partnerships and hence win more business.

In regard to the proposed approach for supply chain design under sustainability metrics, decision-makers will have at hand a set of possible configurations to be chosen in order to comply with environmental and social regulations without neglecting economic performance. Indeed, the agro-industrial sector is prone to high impacts of supply chain and logistics decisions in terms of social and environmental performance, and so the dairy sector of emerging economies, in particular.

With the proposed approach and the implemented models, decision makers do have a rigorous approach to identify and measure sustainability while designing supply chains. The main outcomes of the study include the following:

- A systematic approach, based on the integration of the three dimensions of sustainability,
- A sector-focused methodology for measure social, environmental and economic metrics when designing supply chains,

Besides the actual evaluation of such three dimensions sustainability through tangible metrics, there is some interesting learning through the process:

- The objectiveness of the measuring process allows for proper and clear communication with decision makers regarding the impact
- Enables new tools and processes to support current sustainability programs of agro-industrial companies
- Defines an objective baseline to measure in preparation of future regulations or evolutions of the day-to-day operations
- Validates defined areas of opportunity where decision makers have direct control to evaluate sustainability along the supply chain.

Another important implication of this research was the importance of well-defining a bound for the sustainability metrics in regard to the agents of the supply chain. Indeed, inspired by the ideas proposed by Montoya-Torres et al. (2015), the importance of defining an efficient frontier for sustainability measurement in supply chain design is threefold:

(1) Evaluation of the baseline situation in terms of the system's efficiency relative to costs and environmental and social impacts.
(2) Determination of the trade-offs between the resulting environmental impact and costs, social impacts and costs, and environmental and social impacts, along the supply chain.
(3) Evaluation of the necessity of policies and efficiency assessment of different legislations.

Although focused on a case study on the agri-food sector, the approach proposed in this paper can be easily generalized for other industry sectors. Social and environmental metrics evaluated in the model can be adapted to this end.

## 8 Conclusions and future research

This paper presented a multi-objective optimization model incorporating the three dimensions of sustainability for supply chain network design. In contrast to traditional approaches from the literature for supply chain design, which have focused on the optimization of economic and productive related metrics or only on environmental impact, this paper addressed the three dimensions of sustainability. A case-study research in the dairy sector was taken as an exemplary application, coming from the central region of Colombia. The model addressed explicitly strategic and tactical decisions while considering the minimization of the total costs (economic dimension), the minimization of $CO_2$e emissions at both processing facilities and transport (environmental dimension), and two factors in the categories of work conditions and societal development (social dimension). We use a Chebyshev Goal Programming method to present a solution balancing the undesirable deviations of targets for every single objective. The results showed the existent trade-offs between the three dimensions of sustainability. The defined targets are ambitious in itself. The unweighted balance results give more priority to the social dimension, which obtains the least deviation, thus affecting the environmental performance of the chain. In regard to the proposed approach for supply chain design under sustainability metrics, decision-makers will have at hand a set of possible configurations to be chosen in order to comply with environmental and social regulations without neglecting economic performance. Indeed, the agro-industrial sector is prone to high impacts of supply chain and logistics decisions in terms of social and environmental performance, and so the dairy sector of emerging economies, in particular.

This work is an example of the application of the analytical model to strategic and tactical decisions in the agri-food industry. In practice, the analysis carried out in this paper does help decision-makers of the dairy sector to contribute to the achievement of the sustainable development goals (SDGs). The proposed model and solution approach has however some

limitations that allow extensions in further research. Indeed, results show how location and allocation decisions might have an impact on sustainable development. However, it pops up different inquiries, for instance, although new supply chain structures could entail GHG emissions savings. A first question to be addressed might be: how much improvement is needed to consider the new structure as sustainable? Moreover, since most research works have addressed the evaluation of already constituted supply chains, another question can be: how long does it take to go from the actual structure to the desirable structure? These questions are related with the definition of sustainable development and do highlight the importance of the definition of objectives at assessing sustainability in any system. In such context, for instance, future works might consider models with multiple periods to exemplify the execution of activities in the long-term leading to a stable state in the sustainability indicators of the chain. Also, considering the rise in the definition of national and continental plans to the reduction of GHG emissions and the improvement of social health and living conditions, it makes sense to establish expected values to the sustainability objectives considering information from outside the company, considering supply chains as part of community development.

**Availability of data and material** Not applicable.

**Code availability** Not applicable.

## Declarations

**Conflicts of interest** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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