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ABSTRACT: In this paper, the environmental impact of operating a supply chain of a Fast Moving Consumer Goods (FMCG) company over a one year horizon is considered. The environmental impact is evaluated using the Eco-indicator 99. In the optimization of the tactical planning decisions both this environmental objective and the total costs are considered using the ε-constraint method for identifying a set of Pareto-optimal solutions. For a case study containing 10 Stock-Keeping Units (SKUs), which was optimized with a 1% optimality tolerance, the environmental impact could be reduced by 2.9% without increasing the total costs. A further reduction of environmental impact of up to 6.3% was possible at an increase in total costs of 5.2%. An SKU decomposition algorithm was applied to optimize a larger case study containing 100 SKUs.

1. Introduction

Traditionally, optimization models developed in the process systems engineering community have focused on maximizing an economic performance indicator while considering the process or supply chain limitations (Bojarski et al., 2009). However, starting with the Brundtland (1987) report, an ever-growing pressure from government regulators, non-governmental organizations, and the market itself towards a more environmental-friendly management has led to an increased interest in the sustainable operation of the supply chain in both academia and industry (Hassini et al., 2012). Moreover, improving the environmental performance has been identified as a method of increasing profitability (Barbosa-Póvoa (2009) and Kumar et al. (2012)).

The incorporation of environmental objectives into supply chain management has recently led to a new discipline known as Green Supply Chain Management (GrSCM). Srivastava (2007), Grossmann and Guillén-Gosálbez (2010), and Hassini et al. (2012) review this research area. One of the main challenges identified in these reviews is the definition of a suitable environmental performance indicator. Cano-Ruiz and McRae (1998) have given an extensive review on the various environmental performance indicators that have been used in literature. They identified two main questions concerning the evaluation of alternative solutions. The first question is: how should an alternative be evaluated from an environmental point of view?

Currently, researchers have not yet reached a consensus on the most suitable environmental metric (Grossmann and Guillén-Gosálbez, 2010). In fact, some authors (Srivastava (2007) and Cano-Ruiz and McRae (1998)) argue that given the diverse views regarding the environment, it is unlikely that an agreement on the most suitable environmental metric will ever be reached. Nevertheless, it has become clear that these environmental metrics should be analyzed over the complete life cycle of a product or activity (Grossmann and Guillén-Gosálbez, 2010). In such a Life-Cycle Assessment (LCA), which is described in a series of ISO documents (2006a), the total energy and materials used and the waste released to the environment are quantified over the full life-cycle of a product or process. Based on this information, the environmental impact of a product or activity can be determined.

The Eco-indicator 99 is an aggregate indicator that can be used to evaluate the total environmental impact of a product or activity over its complete life-cycle (Pré consultants B.V, 2001). This indicator introduces a damage function approach that determines the environmental impact based on the damage to human health, resource and ecosystem. In this methodology, first an inventory is made of all emissions, resource extractions and land-use throughout the life cycle of a product. Secondly, based on this information, the damage caused to human health, ecosystem quality and resources is determined. Finally, these damages are weighted into a single indicator. These weights have been determined in a social study performed by the authors of the Eco-indicator 99 (Pré consultants B.V, 2001). This indicator has, for example, been used by Hugo and Pistikopoulos (2005), Guillén-Gosálbez et al. (2008), and Pinto-Varela et al. (2011) to evaluate the environmental impact when optimizing the design and strategic planning of a supply chain.

The second main question identified by Cano-Ruiz and McRae (1998) is: how should this environmental objective be balanced with other objectives? Or, for the problem described in this paper, how should the environmental impact be balanced with the economic costs? There are two main methods of dealing with such a bi-criterion optimization: 1) transform the objectives into a single objective, 2) solve the problem as a bi-criterion optimization problem by determining a set of Pareto-optimal or non-inferior solutions (Grossmann and Guillén-Gosálbez, 2010).

Yakovleva et al. (2012), for example, evaluate the overall performance of potato and chicken supply chains by combining economic, environmental and social indicators into a single overall sustainability index. The advantage of merging the objective functions is that only a single solution will be obtained. This obviates the need to compare the various solutions that could be obtained from a bi-criterion optimization. In addition, this single solution can typically be obtained substantially faster than a range of solutions. Nevertheless, it is difficult to determine a-priori how to properly combine the various objectives. Or specifically for this case, it is difficult to assign an economic cost to the environmental impact. Moreover, having a set of solutions might be more enlightening to the decision-maker rather than having a single solution.

The ε-constraint method can be used to generate a set of non-inferior solutions (Cano-Ruiz and McRae, 1998). A non-inferior, or Pareto-optimal solution, can be defined as a feasible solution to a multi-objective problem to which no other feasible solutions exist that will improve at least one objective without worsening at least one other objective (Cohon, 2003).

When using this method for a bi-criterion optimization, the two objectives are first optimized separately. This will yield minimum and maximum values for both objectives. In the ε-constraint method, one of the objectives is then optimized while considering the other objective as a variable that must be constrained to a certain value ε. Various points of the Pareto curve can then be obtained by varying the value of ε. While this method can be complex and time consuming if the number of objectives is large, it is straightforward for a bi-criterion optimization. The ε-constraint method has, for example, been used by You and Wang (2011) to optimize both economic and environmental objectives in the design of a biomass-to-liquid supply chain, and by Mele et al. (2011) to evaluate economic and environmental objectives in the design of a fuel supply chain based on sugar cane in Argentina.

A considerable amount of research has been done on LCA of industrial food products, and this research area has been reviewed by Roy et al. (2009). However, the results of these LCA are rarely combined with mathematical programming techniques. In fact, in their review on quality, safety and sustainability in food systems, Akkerman et al. (2010) conclude that "sustainability does not seem to have gotten any attention at the distribution network planning level". Therefore, the goal of this paper will be to implement the environmental impact into a tactical planning model for the FMCG industry that was developed in previous work. The environmental impact will be evaluated using the Eco-indicator 99. The environmental and economic objectives will both be considered in the resulting model using the ε-constraint method.

The remainder of this paper is organized as follows. Section 2 gives the problem definition, which is similar to the problem definition of van Elzakker et al. (2014) with the addition of the environmental impact. The base MILP model is discussed in Section 3. In Section 4, the environmental impact of the various operations is evaluated.

Section 5 discusses the ε-constraint method, which is used to generate an approximation of the Pareto curve of the trade-off between economic costs and environmental impact. The results are discussed in Section 6. Finally, conclusions are drawn in Section 7, and the nomenclature is given at the end of the paper.

2. Problem Definition

Given is a supply chain of a FMCG company consisting of suppliers, factories, warehouses, distribution centers and retailers. The location and capacity of these facilities is known. A given set of SKUs has to be produced and distributed through this supply chain. A forecast of the weekly demand of each SKU is given. No backlog of demand is allowed. The demand should thus either be met in the week in which it occurs, or a missed sales penalty will be incurred.

The production process consists of a two-stage make-and-pack production process. The production capacities of both stages, denoted as mixing and packing stages respectively, are known per type of mixing/packing line for each factory. Each SKU belongs to a mixing family that can be produced on a certain type of mixing lines. Similarly, each SKU also belongs to a packing family which can be packed on a certain type of packing lines. Finally, each SKU belongs to an SKU family, which is a set of SKUs with similar production characteristics. When switching from one SKU to the next, a sequence-dependent changeover is required. These sequence dependent changeovers can be approximated using SKU and SKU family set-ups (van Elzakker et al., 2014). The mixing/packing rates and the recipes are known for all SKUs.

The availability of ingredients is known for each supplier for each week. The initial inventory and the storage capacity of ingredients at the factories and of SKUs at the warehouses and distribution centers is known as well. The minimum safety stock is also given for each SKU in all warehouses and distribution centers. All the tactical planning decisions should be considered over a one year horizon divided into weekly periods to cover the seasonality. The transportation times are generally considerably shorter than one week, and therefore, the lead times are assumed to be zero.

The first objective is then to minimize the total costs. These total costs consist of the procurement costs, storage costs, transportation costs, set-up costs, safety stock violation costs and missed sales costs. All these cost factors are given as well. The minimization of the environmental impact is included as a second objective to this problem. This environmental impact can be calculated based on given information about the environmental impact of ingredients, transportation and production. These environmental impacts depend on both the products and the location. Ice cream has been selected as the example product in this paper, and the supply chain is based in Europe.

3. Tactical Planning Model

The base tactical planning problem considered in this paper is the same as the problem we described in van Elzakker et al. (2014). Therefore, we will use the Mixed Integer Linear Programming (MILP) model roposed in that paper as the basis of this model. We will first briefly explain this model and then we will discuss the implementation of the environmental impact into the model.

$$\sum_{f} TransIng_{h,f,s,t} \leq MaxSupply_{h,s,t} \quad \forall h,s,t \tag{1}$$

$$\sum_{h} INVIng_{h,f,t} \leq INVIngCap_{f} \quad \forall f,t \tag{2}$$

$$INVIng_{h,f,t} = INVIng_{h,f,t-1} + \sum_{s} TransIng_{h,f,s,t} - \sum_{i} \left(Recipe_{h,i} \cdot Prod_{i,f,t} \right) \quad \forall h,f,t \tag{3}$$

$$\sum_{\left(i\,\in\,IM_{mfam}\right)} \frac{Prod_{i,f,t}}{MixRate_{i,f}} \le MixTime_{mfam,f} \quad \forall mfam, f,t \tag{4}$$

$$\sum_{i\in IP_{pfam}} \left(\frac{Prod_{i,f,t}}{PackRate_{i,f}} + SUT_i \cdot WSU_{i,f,t} \right) + \sum_{fam\,\in\,FAM_{pfam}} \left[FamSUT_{fam} \cdot YFamSU_{fam,f,t} \right] \le PackTime_{pfam,f} \quad \forall pfam, f,t \tag{5}$$

$$\frac{Prod_{i,f,t}}{PackRate_{i,f}} \le PackTime_{pfam,f} \cdot WSU_{i,f,t} \quad \forall i \in IP_{pfam}, pfam, f,t \tag{6}$$

$$YFamSU_{fam,f,t} \ge WSU_{i,f,t} \quad \forall i \in IF_{fam}, fam, f,t \tag{7}$$

$$\sum_{w} TransFW_{i,f,w,t} = Prod_{i,f,t} \quad \forall i, f,t \tag{8}$$

$$\sum_{i} INVWH_{i,w,t} \le WHCap_{w} \quad \forall w,t \tag{9}$$

$$\sum_{i} INVDC_{i,dc,t} \le DCCap_{dc} \quad \forall dc,t \tag{10}$$

$$INVWH_{i,w,t} = INVWH_{i,w,t-1} + \sum_{f} TransFW_{i,f,w,t} - \sum_{dc} TransWDC_{i,w,dc,t} \quad \forall i,w,t \tag{11}$$

$$INVDC_{i,dc,t} = INVDC_{i,dc,t-1} + \sum_{w} TransWDC_{i,w,dc,t} - \sum_{r} TransDCR_{i,dc,r,t} \quad \forall i,dc,t \tag{12}$$

$$SSVioWH_{i,w,t} \ge SSWH_{i,w,t} - INVWH_{i,w,t} \quad \forall i,w,t \tag{13}$$

$$SSVioDC_{i,dc,t} \ge SSDC_{i,dc,t} - INVDC_{i,dc,t} \quad \forall i,dc,t \tag{14}$$

$$\sum_{dc} TransDCR_{i,dc,r,t} \le D_{i,r,t} \quad \forall i,r,t \tag{15}$$

$$MissedSales_{i,r,t} \ge D_{i,r,t} - \sum_{dc} TransDCR_{i,dc,r,t} \quad \forall i,r,t \tag{16}$$

$$
\begin{aligned}
\text{Min } TotalCosts = & \sum_{h,f,s,t} TransIng_{h,f,s,t} \cdot \left(CostIng_{h,s,t} + TCSF_{f,s} \right) \\
& + \sum_{h,f,t} INVIng_{h,f,t} \cdot SCIng_{h,f} + \sum_{i,w,t} INVWH_{i,w,t} \cdot SCWH_{i,w} + \sum_{i,dc,t} INVDC_{i,dc,t} \cdot SCDC_{i,dc} \\
& + \sum_{i,f,w,t} TransFW_{i,f,w,t} \cdot TCFW_{f,w} + \sum_{i,w,dc,t} TransWDC_{i,w,dc,t} \cdot TCWDC_{w,dc} \\
& + \sum_{i,dc,r,t} TransDCR_{i,dc,r,t} \cdot TCDCR_{dc,r} \\
& + \sum_{i,w,t} SSpenCost \cdot SSVioWH_{i,w,t} + \sum_{i,dc,t} SSpenCost \cdot SSVioDC_{i,dc,t} \\
& + \sum_{i,f,t} SUCost_i \cdot WSU_{i,f,t} + \sum_{fam,f,t} FAMSUCost_{fam} \cdot YFAMSU_{fam,f,t} \\
& + \sum_{i,r,t} MSpen_{i,r,t} \cdot MissedSales_{i,r,t}
\end{aligned}
\tag{17}
$$

The procurement is limited by the available supply in constraint (1). The total ingredient inventory is limited by the capacity in constraint (2) and the ingredient inventory balance is given in constraint (3). The production is limited by the available mixing and packing times through constraints (4) and (5). If an SKU is produced, there must be a set-up of this SKU (constraint (6)). If there is a set-up of at least one SKU of an SKU family, there must be an SKU family set-up (constraint (7)). The total weekly production of each factory must be sent to the warehouses (constraint (8)). Constraints (9) and (10) limit the inventory in warehouses and distribution centers to the storage capacity. The inventory balances of the warehouses and distribution centers are given in constraints (11) and (12). The safety stock violations are determined in constraints (13) and (14). Constraint (15) limits the total amount of each SKU sent to each retailer by the demand. The missed sales is the retailer demand minus the amount sent to the retailer (constraint (16)). As is shown in (17), the original objective of the model is to minimize the total cost which is the sum of the procurement, inventory, transportation, safety stock violation, set-up, and missed sales costs. For a more detailed description of this model we refer the reader to van Elzakker et al. (2014).

4. Environmental Impact

As discussed in the introduction, the environmental impact will be evaluated using the Eco-indicator 99, which is a system based on LCA. This section will discuss the boundaries of the system and the environmental impact of all processes.

4.1. Ingredients

For the ingredients, the environmental impact is analyzed based on the two main ingredients of ice cream: milk and sugar. For the ingredients, it is assumed that the majority of the environmental impact is due to greenhouse gas (GHG) emissions and energy consumption. Kristensen et al. (2011) evaluated the environmental performance of 67 European dairy farms using an LCA based on GHG emissions expressed in kg CO_2 equivalent. Their LCA included both on-farm and off-farm emissions. The off-farm emissions were due to imported resources such as feed and fertilizer.

Since many of the farms produce both milk and meat, the GHG emissions of the farm must be allocated between the milk and meat. Kristensen et al. (2011) use several allocations methods. Using an allocation based on the amount of milk and meat proteins produced, which was the method recommended by the Food and Agriculture Organization of the United Nations - Animal Production and Health Division (2010), they report GHG emissions ranging between

0.83 and 1.31 kg CO_2 equivalent per kg energy corrected milk (ECM). The amount of ECM can be calculated based on the fat and protein percentages of the milk.

The environmental impact of milk production is also evaluated in a report by Williams et al. (2006). They compare organic to non-organic farming. The main advantage of the organic farming is the strong reduction in primary energy usage from 2.52 to 1.56 MJ/l. On the other hand, the GHG emissions increase from 1.06 to 1.23 kg CO_2 equivalent per liter. These GHG emissions are in the same range as those reported by Kristensen et al. (2011). Since they did not report the energy usage, the data reported by Williams et al. (2006) will be used for both GHG emissions and energy usage. A milk density of 1.03 kg/l has been used to convert the impact per liter to the impact per kilogram.

A recent study by the European Association of Sugar Producers (CEFS) (Klenk et al., 2012a, 2012b) evaluated the product carbon footprint (PCF) of sugar. The PCF of EU beet white sugar ranged from 0.300-0.643 kg CO_2 equivalent per kg sugar when using the substitution method. This substitution method is the preferred method for co-product accounting according to ISO EN 14044:2006 (2006b). The PCF of sugar refined in the EU from imported raw cane sugar ranged between 0.642-0.760 kg CO_2 equivalent per kg sugar. Seabra et al. (2011) report that the net fossil energy use is 721 kJ per kilogram of sugar from Brazilian sugar cane. They calculate the GHG emissions to be 0.234 kg CO_2 equivalent/kg sugar. This value is significantly lower than the range reported by Klenk et al. (2012a, 2012b) since it does not include the overseas transport and refining. Therefore, we will use the PCF from the CEFS report. The primary energy consumption of beet sugar was not reported in any of the papers or reports. Therefore, it is assumed to be equal to the primary energy consumption of cane sugar.

The environmental impact in Eco-indicator 99 units can then be calculated. The environmental impact is 0.00544 ECO 99 units/kg CO_2 according to the database of the Center for environmental assessment of product and material systems (CPM, 2013). The primary energy use mainly consists of diesel, electricity and gas. The environmental impact of the primary energy use has been estimated based on the average environmental impact of producing 1 kWh of electricity in Europe, which is 0.027 ECO 99 units according to the addendum of the Eco-indicator 99 manual for designers (Pré consultants B.V., 2003). The calculated environmental impacts of milk and sugar are given in Table 1.

Table 1. Environmental impact of milk and sugar

	Non-Organic Milk	**Organic Milk**	**Beet Sugar**	**Cane Sugar**
Emissions				
[kg CO2-eq/t product]	1029	1194	471*	701*
[ECO 99 units/t product]	5.60	6.50	2.56	3.81
Energy Consumption				
[MJ/t product]	2447	1515	721	721
[ECO 99 units/t product]	18.35	11.36	5.41	5.41
Total Impact [ECO 99 units/t product]	24.0	17.9	8.0	9.2

* Based on the average PCF

4.2. Transportation

In the Eco-indicator 99 manual for designers (Pré consultants B.V., 2003), the environmental impact is given for several modes of transportation. We evaluate the environmental impact of transportation based on a 40t truck with a 50% load which, according to the manual, is the European average load. The environmental impact is then 0.015 ECO 99 units/tkm. A tkm represents one tonne of product being transported over a distance of one kilometer.

4.3. Production

Since ice cream is a food product, no hazardous components are used in the production process. Nevertheless, the ice cream production has a considerable environmental impact due to two factors. First, in a report completed by the Manchester Business School for the Department for Environment Food and Rural Affairs (Foster et al., 2006), it was estimated that the production of ice cream consumes approximately 0.65 MJ/kg ice cream. The environmental impact of production then depends on the source of the energy. The energy mix varies greatly between the various European countries. As a result, the environmental impact of one kWh also varies greatly depending on the location. In the addendum of the Eco-indicator 99 manual for designers (Pré consultants B.V., 2003), the environmental impact per kWh is estimated for several European countries. The impact per kWh and the impact per kilogram ice cream produced are given in Table 2.

Table 2. Environmental impact of the ice cream production process

Country	**Environmental impact per kWh** [ECO 99 units/kWh]	**Environmental impact per tonne ice cream** [ECO 99 units/t product]
Austria	0.018	3.25
Belgium	0.024	4.33
Switzerland	0.010	1.81
France	0.012	2.17
Greece	0.062	11.19
Italy	0.048	8.67
the Netherlands	0.037	6.68
Portugal	0.047	8.49

Secondly, the environmental impact due to set-ups on the packing line should also be considered. This environmental impact is approximated with the loss of 0.5 tonne of product per set-up. The environmental impact can then be calculated based on the recipes and the environmental impact of the ingredients. It is assumed that the environmental impact of the product waste itself is negligible for food products.

It should be noted that changeovers on the mixing line have a similar environmental impact. However, the number of changeovers in the mixing line is determined by the factory design rather than the tactical planning decisions (van Elzakker et al., 2014). Therefore, the environmental impact of the mixing line changeovers is not included in the model.

4.4. Storage

Ice cream must be stored at low temperatures. Therefore, a considerable amount of cooling energy is required in the storage stages. However, the amount of cooling energy required depends mainly on the loss of cooling energy to the environment. The loss of cooling energy is independent of the amount in storage and is mostly determined by the facility characteristics, such as the energy efficiency of the cooling system, the size of the facility, the ambient temperature, and the quality of the insulation. These facility characteristics are not influenced by the decisions taken in the tactical planning model.

Therefore, the environmental impact of the storage is not included in the model since it would only add a constant to the objective. It should be noted, however, that it would be important to consider the environmental impact of storage in a strategic planning model. In such a model, the location of the storage facilities and the type of cooling system chosen could greatly influence the environmental impact.

5. The ε -constraint method

The environmental impact discussed in the previous section is added as a second objective to the tactical planning model. This environmental impact, which is minimized, is equal to the sum of the impact of the purchased ingredients, the production, the set-ups, and the transportation.

$$\begin{aligned}
\min EnvImpact = & \sum_{h,s,f,t} EnvImpactIng_{h,s} \cdot TransIng_{h,s,f,t} + \sum_{i,f,t} EnvImpactProd_{f} \cdot Prod_{i,f,t} \\
& + \sum_{i,f,t} EnvImpactSU_{i} \cdot WSU_{i,f,t} \\
& + EnvImpactTrans \cdot \begin{pmatrix} \sum_{h,s,f,t} \left(DistanceSF_{s,f} \cdot TransIng_{h,s,f,t} \right) \\ + \sum_{i,f,w,t} \left(DistanceFW_{f,w} \cdot TransFW_{i,f,w,t} \right) \\ + \sum_{i,w,dc,t} \left(DistanceWDC_{w,dc} \cdot TransWDC_{i,w,dc,t} \right) \\ + \sum_{i,dc,r,t} \left(DistanceDCR_{dc,r} \cdot TransDCR_{i,dc,r,t} \right) \end{pmatrix}
\end{aligned} \tag{18}$$

The ε-constraint method is used to consider both this environmental objective and the cost objective. In the ε-constraint method, the optimum with respect to both objectives is determined first. Therefore, in the first step the economic costs are minimized without considering the environmental impact. The solution obtained in this step might, however, be weakly dominated. That is to say, while no other feasible solutions exist with a lower economic cost, another feasible solution with equal economic costs and a lower environmental impact might exist. Therefore, this minimum cost is used to constrain the economic cost and the environmental impact is minimized. This will yield the minimum economic cost and the maximum environmental impact. While feasible solutions with a higher environmental impact might exist, these will be Pareto inferior and thus suboptimal.

In the second step, the environmental impact is minimized without considering the economic cost. However, the environmental impact can be reduced to zero by not procuring, producing or transporting anything. Clearly, that is an unrealistic solution. Therefore, the requirement is included that the customer service level should be at least equal to the customer service level in the minimum cost solution. This is achieved through the following two constraints. First, the total amount of missed sales must be equal to or less than the total amount of missed sales in the minimum economic cost solution, *MaximumMS*.

$$\sum_{i,r,t} D_{i,r,t} - \sum_{i,dc,r,t} TransDCR_{i,dc,r,t} \leq MaximumMS \tag{19}$$

Secondly, the total safety stock violation must be equal to or less than the total safety stock violation in the minimum economic cost solution, *MaximumSSVio*. These two constraints are included in all optimizations in step 2 and 3 of the ε-constraint method.

$$\sum_{i,w,t} SSVioWH_{i,w,t} + \sum_{i,dc,t} SSVioDC_{i,dc,t} \leq MaximumSSVio \tag{20}$$

Similar to step 1, this environmental impact minimization might yield a weakly dominated solution. Therefore, the environmental impact is constrained to the obtained minimum and the economic costs are minimized. At the end of step 2, lower and upper bounds have been established for both objectives.

In the third step, various solutions between these lower and upper bounds are obtained by constraining one objective and minimizing the other objective. We will minimize the economic cost in this step, while the environmental impact is bound using constraint (21). The ε will be varied between 0 and 1 in increments determined by the number of desired solutions, *NParetoPoints*. For the case studies considered in this paper 26 points are used, which is a sufficient number of points to obtain a good representation of the Pareto front.

$$EnvImpact \leq \varepsilon \cdot EnvImpactLB + (1-\varepsilon)\, EnvImpactUB \tag{21}$$

While it should be noted that these solutions might again be weakly dominated, the possibility for improvement is small if a sufficiently large *NParetoPoints* is used. For example, if the difference between the minimum and maximum environmental impact is 10%, then the difference in environmental impact between consecutive solutions will be 0.4% if 26 points are used. Therefore, if the environmental impact could be reduced by 0.4% or more without increasing the economic costs, it will be covered by the next point on the Pareto front.

The ε-constraint method as implemented in this paper can be summarized as follows:

Step 1

a) Minimize the economic costs given in (17)
b) Limit the economic costs to obtained minimum
c) Minimize the environmental impact given in (18) subject to the limitation from step 1b

Step 2

a) Minimize the environmental impact given in (18)
b) Limit the environmental impact to the obtained minimum
c) Minimize the economic costs given in (17) subject to the limitation from step 2b

Step 3

a) $\varepsilon := \dfrac{1}{NParetoPoints}$
b) Minimize economic cost with the environmental impact bound by constraint (21)
c) $\varepsilon := \varepsilon + \dfrac{1}{NParetoPoints}$
d) Terminate if ε=1, otherwise go to Step 3b

It should be noted that steps 1c and 2c are not always present in the ε-constraint method. These steps are not always necessary since the minimization of one of the objectives might give a unique solution. In that case, adding a bound to this first objective and minimizing the second objective will simply yield the same solution.

However, for the problem discussed in this paper, steps 1c and 2c may improve the second objective. First of all, because a 1% MIP optimality tolerance is used, there will typically be a variety of solutions whose objective is less than or equal to the lower bound obtained in step 1a or 2a. Therefore, a minimization on the second objective may be worthwhile.

Secondly, even when the problem is solved to optimality, the minimum costs and minimum environmental impact solutions might not be unique. For example, the amount of product in storage influences the economic costs but not the environmental impact. As a result, it might be possible to considerably reduce the storage costs of the minimum environmental impact solution without increasing the environmental impact. Therefore, steps 1c and 2c are used in this paper to obtain the true Pareto-optimal extreme points (within a 1% optimality tolerance).

6. Results

The first case study that is considered contains 10 SKUs, 10 ingredients, 52 weekly time periods, and a supply chain consisting of 10 suppliers, 4 factories, 5 warehouses, 10 distribution centers, and 20 retailers. Each SKU belongs to one of 2 different mixing families, 4 packing families and 12 SKU families. The factories are located in Austria, Belgium, Greece, and Portugal, and they contain 16, 16, 8, and 24 packing lines respectively. One warehouse is located near each factory. The location of all other facilities was determined by randomizing the x and y coordinates. If an infeasible location was obtained, such as a location in the middle of a sea, the coordinates were randomized again until a feasible location was obtained. The transportation distance between two locations is estimated as the straight line distance between the locations.

The various recipes of ice cream are assumed to contain approximately 65-75% milk based ingredients, such as milk and cream, and 15-20% sugar. The environmental impact of all milk based ingredients is assumed to be equal to the environmental impact of milk. Because the other ingredients only account for a small percentage of the recipe, the environmental impact of the other ingredients was not considered.

Due to the extremely large amount of data required and due to confidentiality, hypothetical data is used for all other parameters. Most data is generated from uniform distributions where the lower and upper bounds are the best estimates for the range of the parameter. For example, the uniform distribution $U(x,y)$ is used to generate the ingredient purchasing cost, where x to y is the best estimate for the range of the price of a certain ingredient.

However, there are a few notable exceptions. Each mixing/packing line has a capacity of 120 hours per week, and therefore, the available mixing/packing time is generated from a discrete uniform distribution. In addition, the capacity of the packing lines is aligned with the capacity of the mixing lines to ensure that the production capacity of a mixing family is similar to the packing capacity of the related packing families.

The total demand of the SKUs is generated based on the production capacity and a utilization percentage, which is determined from a uniform distribution. Since many FMCG are seasonal, 80% of the total demand is allocated to the peak demand between weeks 39 and 48. Each SKU has a 33% chance to be sold at a retailer. Similarly, each ingredient has a 25% chance to be sold at a supplier.

The total availability of ingredients is determined from the ingredient demand, which can be calculated from the SKU demand and the recipes, and a utilization percentage that is generated from a uniform distribution. The upper and lower bounds of the uniform distribution of the storage capacities and the safety stock levels are determined based on the total demand.

All optimizations are performed using CPLEX 12.4 in AIMMS 3.12 on a computer with an Intel(R) Core(TM) i7-3770 CPU @ 3.40 Ghz and with 16 GB of memory. All optimizations are performed with a one percent MIP optimality tolerance.

6.1. Full space model

For the 10-SKU case study, the model contains 185,538 variables, 2,080 binary variables, and 41,761 constraints. The required CPU time was 8403 seconds with an *NParetoPoints* of 26. In other words, the economic costs were minimized for 24 maximum environmental impacts which were distributed equally between the two extremes obtained in the first two steps of the ε-constraint method.

In step 1a, the minimum economic costs were determined to be €368.1M and the environmental impact of the obtained solution was 12.5M ECO 99 points. In steps 1b and 1c, this environmental impact was then reduced to 12.1M ECO 99 point by adding the €368.1M as upper bound of the economic costs and then minimizing the environmental impact. The environmental impact could thus be reduced by 2.9% without increasing the economic cost.

In step 2a, the minimum environmental impact was determined to be 11.4M ECO 99 units with an economic cost of €402.0M. In steps 2b and 2c, the economic cost could be reduced to 387.2M. This represents a cost saving of 3.8% without an increase in environmental impact. The scope for reducing the costs of this minimum environmental impact solution is this large because the inventory does not have an environmental impact. As a result, the inventory build-up starts unnecessarily early in the initial minimum environmental impact solution. In fact, 89% of the cost saving is due to the decrease in inventory costs.

In step 3, other points on the Pareto front were generated. However, because of the 1% optimality gap, some solutions were dominated by other solutions. This can be explained using Figure 1. The green points are lower bounds, while the orange points are the obtained solutions. All solutions are within the specified optimality tolerance. However, the obtained optimality gap is not constant. Solution D has a small optimality gap, whereas solution C has a considerably larger optimality gap. As a result, both the economic cost and the environmental impact of solution D are lower than those of solution C. Since these dominated solutions are inferior to those on the Pareto front, they will not be shown in the remainder of this paper.

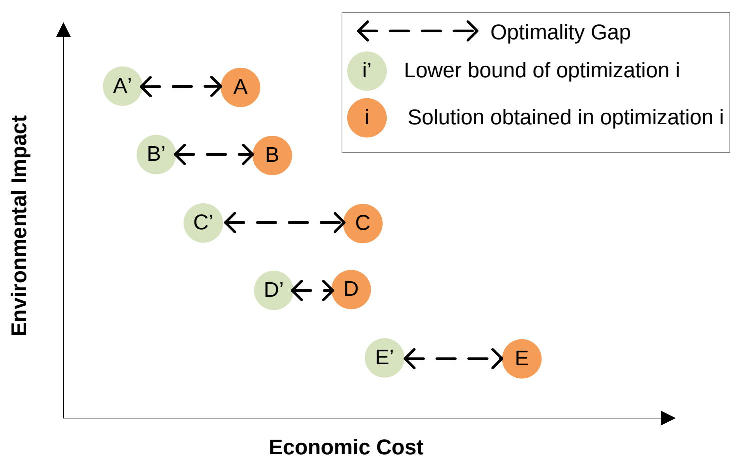

Figure 1. Example of a dominated solution (point C) because of a larger optimality gap

The Pareto front obtained in step 3 is shown in Figure 2. The cost increase for the more environmentally friendly solutions is mainly caused by more expensive ingredients and higher inventories. When comparing the minimum economic costs solution with the minimum environmental impact solution, 75.7% of the cost increase is due to ingredient procurement, 23.6% due to inventory costs, and 0.7% due to set-up costs. On the other hand, the transportation costs decrease by 4.6% in the minimum environmental impact solution.

The procurement costs increase because more expensive ingredients are preferred because they are either closer to the factory, and thus decrease the environmental impact of transportation, or because the ingredient type has a lower environmental impact. The effect of this second factor is clearly demonstrated in Figure 3, which shows that for the lower economic costs solutions non-organic milk is preferred over organic milk. With increasing economic costs, and thus a decreasing environmental impact, the quantity of organic milk that is procured increases. On the other hand, the percentage of sugar from sugar beets and sugar cane remains constant, as can be seen in Figure 4. This is mainly because the difference in environmental impact is smaller, and therefore the environmental impact of transportation becomes a more decisive factor.

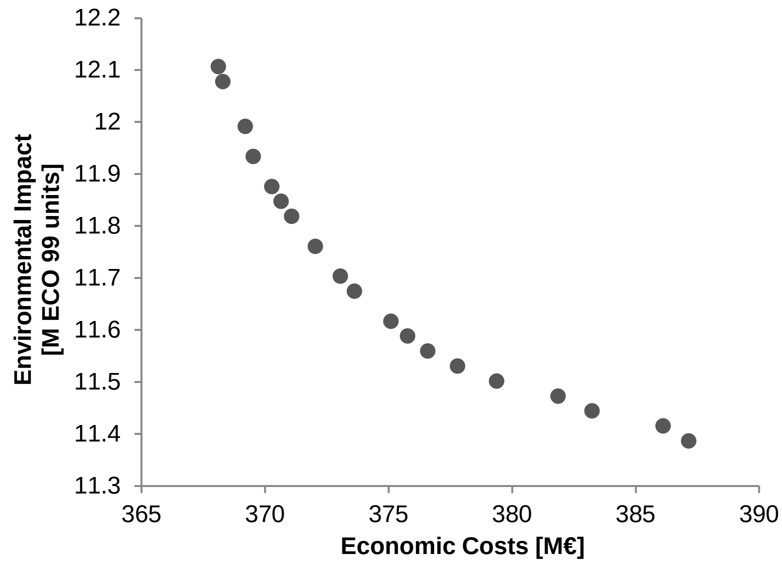

Figure 2. Trade-off between economic and environmental performance

The inventory costs increase for the more environmentally friendly solutions because it allows the SKUs to be produced in factories with a lower environmental impact. In the minimum economic cost solution, the SKUs are typically produced close to the demand date to decrease the inventory costs and near the demand location to decrease the transportation costs. While producing near demand locations reduces the environmental impact of transportation, the environmental impact of the energy mix plays an important role in the minimum environmental impact solution as well. The distribution of production between the factories is given in Figure 5.

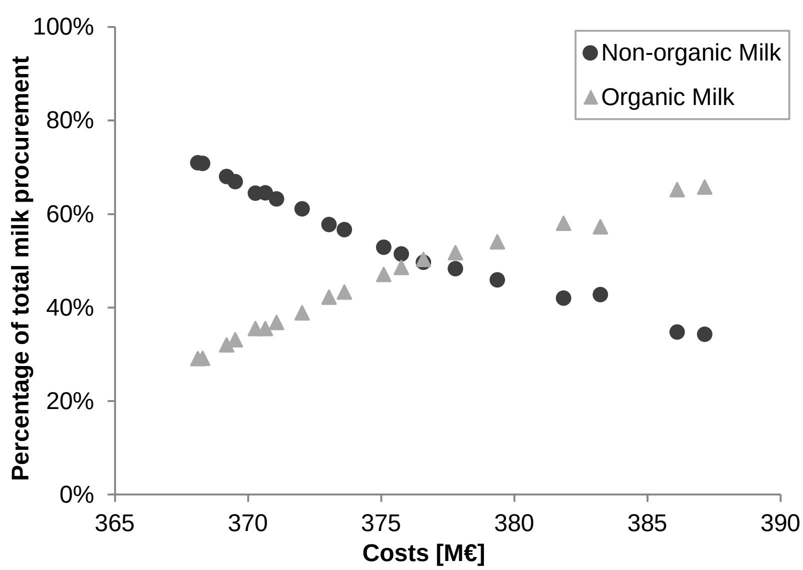

Figure 3. Percentage of organic and non-organic milk versus the total costs

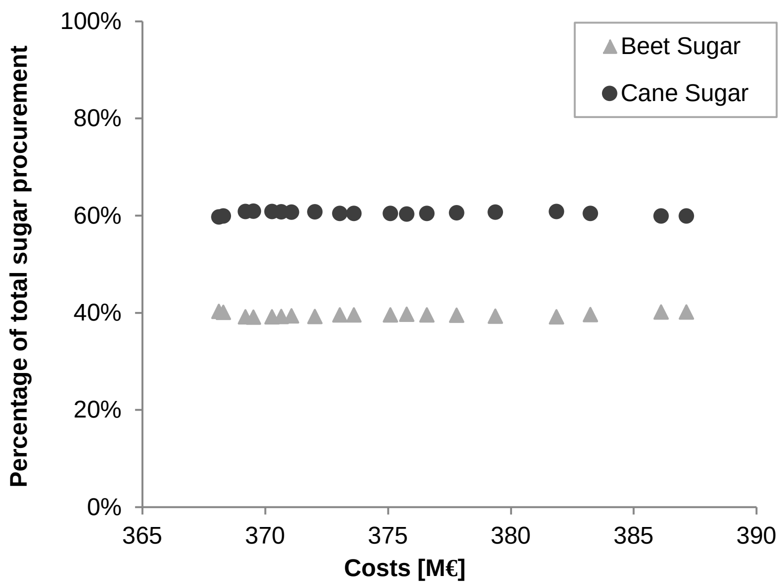

Figure 4. Percentage sugar from sugar beets and sugar cane versus the economic costs

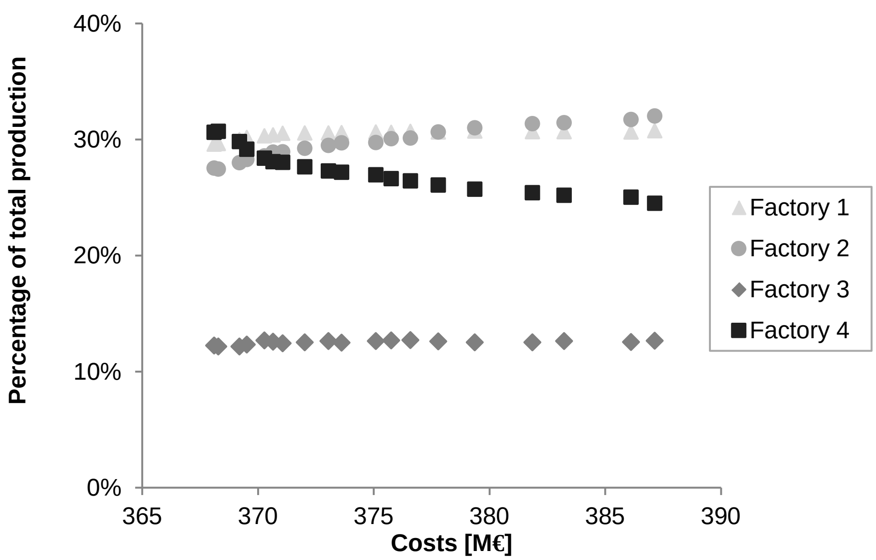

Figure 5. Total production in each of the 4 factories versus the total costs

The main trend is that in the solutions with a lower environmental impact part of the production of factory 4 is moved to factory 2, which has a more environmentally friendly energy mix. It should be noted that factories 1 and 2 are close to their maximum capacity in the solution with the minimum environmental costs. As a matter of fact, factory 1 is close to its maximum capacity in all solutions due to its central location and environmentally friendly energy mix.

Finally, the set-up costs increase slightly because the environmental impact of these set-ups is very small. They account for only 0.02% of the total environmental impact in all solutions. An overview of the environmental impact of the minimum environmental impact and minimum economic cost solutions is given in Figure 6. The switch from non-organic to organic milk accounts for 53.4% of the decrease in environmental impact. The on average shorter transportation distances account for 38.2%, and the production in locations with a more environmentally friendly energy mix account for 8.4%. Interestingly, 80.2% of the reduction in environmental impact of transportation occurs in the transportation of ingredients. The optimal procurement decisions depend strongly on the objective; shorter transportation distances are preferred when minimizing the environmental impact, while less expensive ingredients are preferred when minimizing the costs. On the other hand, the transportation distances are the most important factor for both objectives in the transportation decisions in the rest of the supply chain.

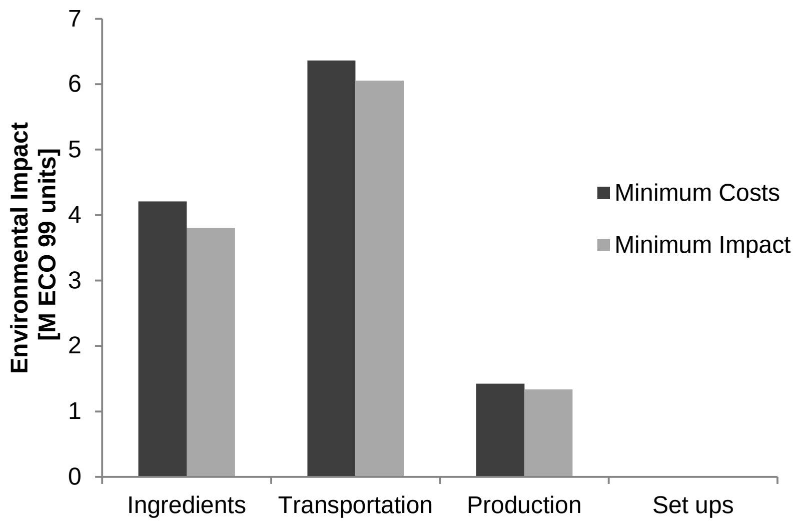

Figure 6. Comparison of the environmental impact of the minimum cost and minimum impact solutions.

6.2. SKU Decomposition algorithm

While the 10-SKU case study could be optimized within a reasonable time using the full space model, the model becomes intractable for larger case studies. In van Elzakker et al. (2014), we proposed an SKU decomposition algorithm to be able to optimize more realistically sized problems. The algorithm can be summarized as follows.

In the algorithm, the model is decomposed into single SKU submodels. These submodels are optimized sequentially to obtain an initial solution. The capacity that is used by the other SKUs is introduced into these submodels as a parameter. Capacity violations are initially allowed using slack variables, which are introduced into the objective function with a penalty cost. Initially these penalty costs will be low, and therefore most likely an infeasible initial solution will be obtained. However, in subsequent iterations the penalty costs are slowly increased, which will make the capacity violations more expensive and which will force SKUs to be reallocated. Eventually, the penalty cost will be sufficiently high such that a feasible solution is obtained. A more detailed description of the algorithm is given in van Elzakker et al. (2014).

While the algorithm offers no guarantee of optimality, we showed that for a variety of case studies solutions within a few percent of optimality can be obtained using the algorithm. Moreover, we could optimize case studies of up to 1000 SKUs using the SKU decomposition algorithm whereas the full space model was intractable for case studies containing more than 25 SKUs. The implementation of the SKU decomposition algorithm in this paper is similar to that discussed in van Elzakker et al. (2014) with the following additions.

Constraints (19) and (20), which limit the amount of missed sales and safety stock violation, are applied for each individual SKU. Constraint (21), which limits the environmental impact, must be treated as a capacity constraint. That is to say, a slack variable should be introduced to the right hand side to initially allow this constraint to be violated at a penalty cost. This slack variable is added to the objective function. Since this slack variable is aggregated over all locations and weeks, it will only incur the base penalty cost, which increases per iteration. The updated constraint is:

$$SKUEnvImpact + SKUEnvImpactP \leq \varepsilon \cdot EnvImpactLB + \left(1-\varepsilon\right) EnvImpactUB + \gamma EI \tag{22}$$

Similarly, the bound on the economic costs in step 1b of the ε-constraint method has to be updated as well. The total costs of all decisions influenced by the current SKU, *SKUCosts*, plus the total costs of all decisions that cannot be influenced by the current SKU, *SKUCostsP*, must be less than or equal to the minimum costs obtained in step 1a plus the total costs slack variable. This slack variable will initially allow solutions to exceed the minimum costs. But with increasing penalty costs, violating the minimum economic costs will become more expensive in the environmental objective.

$$SKUCosts + SKUCostsP \leq CostsLB + \gamma TC \tag{23}$$

The 10-SKU case study was optimized using this updated SKU decomposition algorithm and the ε-constraint method. The required CPU time was 5498s versus the 8403s of the full model. A comparison between the results obtained with the algorithm and with the full space model is given in Figure 7. When comparing the minimum economic cost solution obtained using the algorithm with the full space model, the total cost increases by 0.55% and the environmental impact increases by 0.55% as well. When comparing the minimum environmental impact solution, the environmental impact increases by 0.12% and the total costs increases by 0.29%. For all solutions obtained using the full space model, a solution was obtained using the algorithm with lower costs and an environmental impact within 3.00% of the environmental impact of the full space model solution, and/or a solution was obtained with a lower environmental impact and a total costs within 1.24%. Therefore, it can be concluded that the SKU decomposition algorithm still yields solutions within a few percent of optimality when applied in combination with the ε-constraint method.

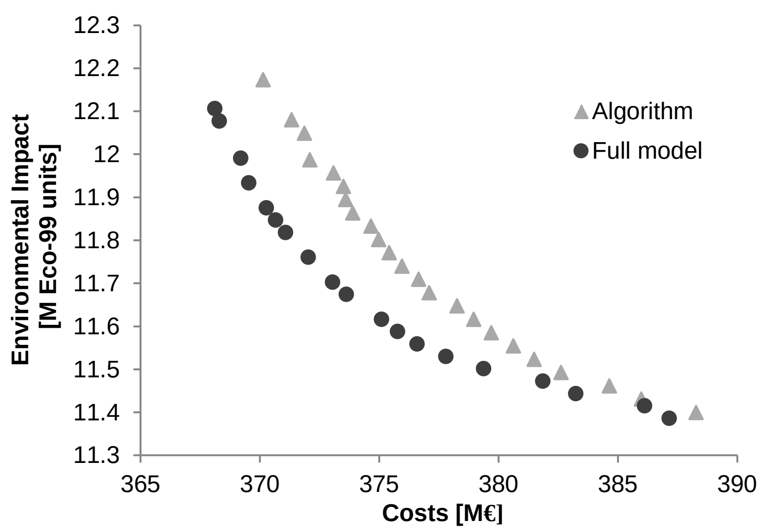

Figure 7. Comparison of the trade-off between economic and environmental performance of the solutions obtained with the full space model and the algorithm

The SKU decomposition algorithm was also used to optimize a larger case study containing 100 SKUs and 6 factories located in Austria, Belgium, Greece, Portugal, Italy, and France. A total computational time of 43 hours is required to optimize this case study using the SKU decomposition algorithm combined with the ε-constraint method. The trade-off between the environmental impact and the economic costs of the obtained solutions is shown in Figure 8. A total decrease in environmental impact of 4.5% could be obtained at an economic cost increase of 5.2%.

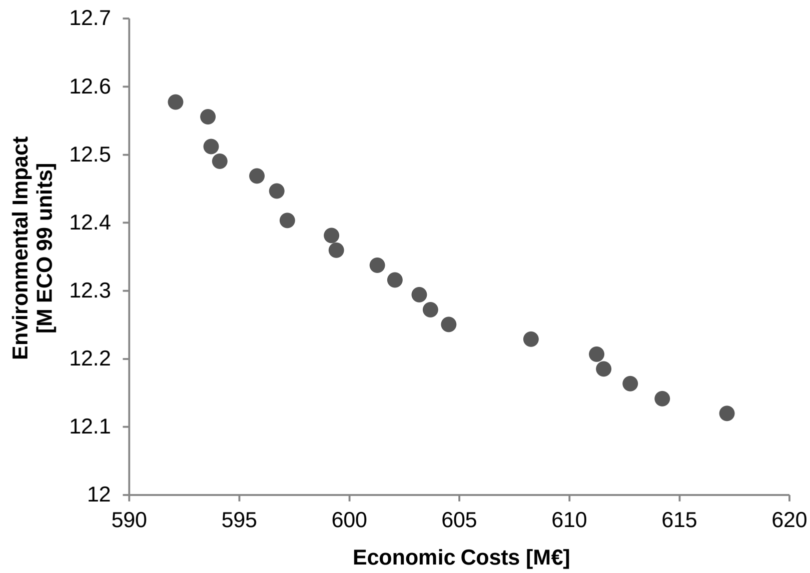

Figure 8. Trade-off between environmental and economic performance of the solutions obtained using the SKU decomposition algorithm for the 100-SKU case study.

As shown in Figure 9 and similar to the 10-SKU case study, a significant part of the reduction in environmental impact is obtained by increasing the percentage of organic milk from 49% to 73%. Also similar to the 10-SKU case study, the percentage of beet sugar remains approximately constant in all solutions.

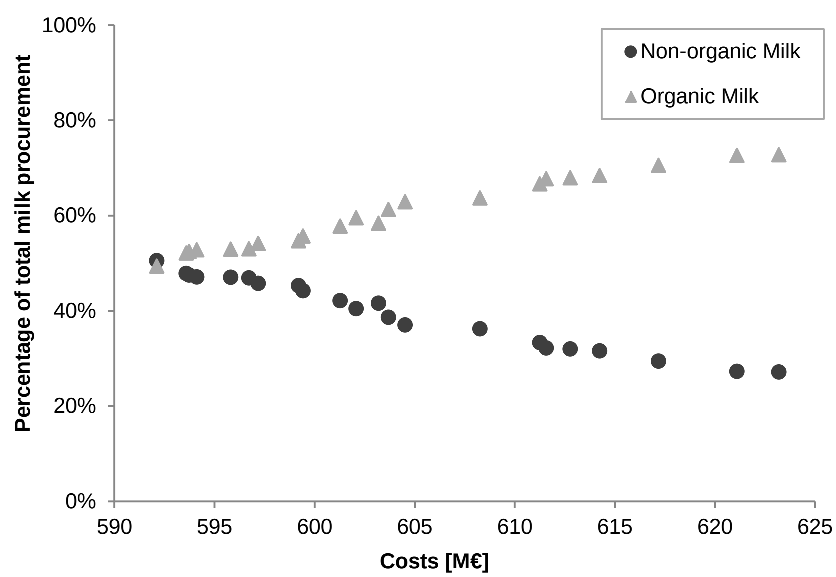

Figure 9. Percentage of organic and non-organic milk versus the total costs for the 100-SKU case study

The factories can be divided into two groups. The factories in Austria (3.25), Belgium (4.33), and France (2.17) have an energy mix with a low environmental impact, while the factories in Greece (11.19), Italy (8.67), and Portugal (8.49) have an energy mix with a high environmental impact. The number in parentheses after each location is the environmental impact of the energy consumption related to production in ECO 99 units/t product.

Figure 10 shows that, as would be expected, the production is moved towards the factories with a lower environmental impact energy mix in the more environmentally friendly solutions.

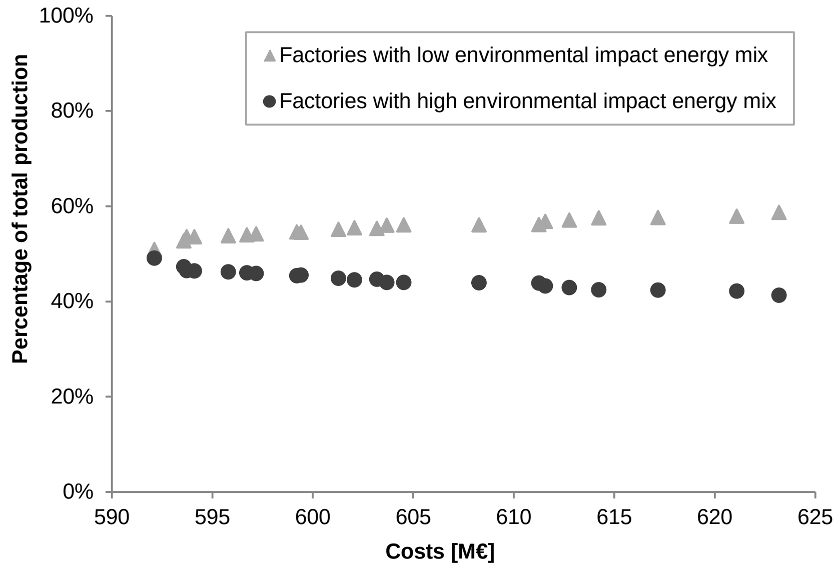

Figure 10. Allocation of production to factories with a low or high environmental impact energy mix versus the total costs for the 100-SKU case study

7. Conclusions

In this paper, the total environmental impact of procurement, production and transportation was considered as a second objective in the optimization of the tactical planning of a FMCG company. It was shown that considering this environmental objective in the tactical planning can be beneficial. In fact, for the 10-SKU case study, which was optimized with a 1% optimality gap, the environmental impact could be reduced by 2.9% without even increasing the economic costs.

In addition, the environmental impact could be reduced further by up to 6.3% at a total cost increase of 5.2%. Using the ε-constraint method, a set of solutions between these two extremes was generated. This allows the decision-maker to select the most desirable solution based on the trade-off between the economic costs and the environmental impact.

More than half of the reduction in environmental impact was achieved by switching to ingredient sources with a lower environmental impact. In addition, more than thirty percent of the reduction was achieved by opting for slightly more expensive ingredients at suppliers closer to the factory. Therefore, it can be concluded that while the environmental and economic objectives align reasonably well for the part of the supply chain between factories and retailers, considerable reductions in environmental impact can be achieved by considering the environmental impact related to supply.

The SKU decomposition algorithm was applied to the bi-criterion tactical planning model. Compared to the full space model, the minimum costs obtained with the algorithm were 0.55% higher, and the minimum environmental impact was 0.12% higher. Overall, the algorithm could obtain solutions similar to the full space model either within 1.24% of the total costs and at a lower environmental impact, or within 3.00% of the environmental impact and at lower costs. Therefore, it can be concluded that the SKU decomposition algorithm can obtain solutions within a few percent of optimality for the bi-criterion model.

8. Nomenclature

8.1. Indices

dc	Distribution centers
f	Factories
fam	SKU families
h	Ingredients
i	SKUs
mfam	Mixing families
pfam	Packing Families
r	Retailers
s	Suppliers
t	Weeks
w	Warehouses

8.1. Subsets

FAM_{pfam}	SKU families belonging to packing family *pfam*
IF_{fam}	SKUs belonging to SKU family *fam*
IM_{mfam}	SKUs belonging to mixing family *mfam*
IP_{pfam}	SKUs belonging to packing family *pfam*

8.2. Parameters

$CostIng_{h,s,t}$	Unit cost of ingredient *h* at supplier *s* in week *t*
CostsLB	Lower bound on the total costs. This lower bound is determined in step 1a of the ε-constraint method.
$D_{i,r,t}$	Demand of SKU *i* in retailer *r* in week *t*
$DCCap_{dc}$	Available storage capacity in distribution center *dc*
$DistanceDCR_{dc,r}$	Distance between distribution center *dc* and retailer *r* in kilometer
$DistanceFW_{f,w}$	Distance between factory *f* and warehouse *w* in kilometer
$DistanceSF_{s,f}$	Distance between supplier *s* and factory *f* in kilometer
$DistanceWDC_{w,dc}$	Distance between warehouse *w* and distribution center *dc* in kilometer
$EnvImpactIng_{h,s}$	The environmental impact associated with the production of one tonne of ingredient *h* from supplier *s*
EnvImpactLB	Lower bound on the total environmental impact. This lower bound is determined in step 2a of the ε-constraint method.
$EnvImpactProd_f$	The environmental impact of producing one tonne of product at factory *f*
EnvImpactTrans	The environmental impact of transporting one tonne of product over one kilometer
$EnvImpactSU_i$	The environmental impact of a set-up to SKU *i*
EnvImpactUB	Upper bound on the total environmental impact. This upper bound is determined in step 1c of the ε-constraint method.
$FAMSUCost_{fam}$	Average set-up cost for SKU family *fam*
$FAMSUT_{fam}$	Average set-up time for SKU family *fam*
$INVIngCAP_f$	Available storage capacity for ingredients at factory *f*
MaximumMS	Upper bound on the total amount of missed sales. This upper bound is determined in step 1c of the ε-constraint method.

MaximumSSVio	Upper bound on the total amount of safety stock violations. This upper bound is determined in step 1c of the ε-constraint method.
$MaxSupply_{h,s,t}$	Available supply of ingredient *h* at supplier *s* in week *t*
$MixTime_{mfam,f}$	Available mixing time at factory *f* for SKUs that are part of mixing family *mfam*
$MixRate_{i,f}$	Mixing rate of SKU *i* in factory *f*
$MSpen_{i,r,t}$	Penalty costs per unit of missed sales of SKU *i* at retailer *r* in week *t*
NParetoPoints	Parameter used to set the number of desired points on the Pareto front
$PackRate_{i,f}$	Packing rate of SKU *i* in factory *f*
$PackTime_{pfam,f}$	Available packing time at factory *f* for SKUs that are part of packing family *pfam*
$Recipe_{h,i}$	Amount of ingredient *h* consumed per unit produced of SKU *i*
$SCIng_{h,f}$	Storage costs of ingredient *h* at factory *f*
$SCDC_{i,dc}$	Storage costs of SKU *i* at distribution center *dc*
$SCWH_{i,w}$	Storage costs of SKU *i* at warehouse *w*
SKUCostsP	Total costs of all decisions that are not influenced by the current SKU
SKUEnvImpactP	Total environmental impact of all decisions that are not influenced by the current SKU
$SSDC_{i,w,t}$	Minimum safety stock of SKU *i* in distribution center *dc* in week *t*
$SSWH_{i,w,t}$	Minimum safety stock of SKU *i* in warehouse *w* in week *t*
SSpenCost	Safety stock violation penalty cost
$SUCost_i$	Average set-up cost for SKU *i*
SUT_i	Average set-up time for SKU *i*
$TCDCR_{dc,r}$	Transportation cost between distribution center *dc* and retailer *r*
$TCFW_{f,w}$	Transportation cost between factory *f* and warehouse *w*
$TCSF_{s,f}$	Transportation cost between supplier *s* and factory *f*
$TCWDC_{w,dc}$	Transportation cost between warehouse *w* and distribution center *dc*
$WHCap_w$	Available storage capacity in warehouse *w*
ε	Parameter used in the ε-constraint method to select an intermediate bound of the environmental impact.

8.3. Nonnegative Continuous Variables

EnvImpact	Total environmental impact of the complete supply chain over a one year horizon
$INVDC_{i,dc,t}$	Amount of SKU *i* stored in distribution center *dc* in week *t*
$INVIng_{h,f,t}$	Inventory of ingredient *h* at factory *f* in week *t*
$INVWH_{i,w,t}$	Amount of SKU *i* stored in warehouse *w* in week *t*
$MissedSales_{i,r,t}$	Shortage of SKU *i* at retailer *r* in week *t*
$Prod_{i,f,t}$	Amount of SKU *i* produced at factory *f* in week *t*
SKUCosts	Total costs of all decisions influenced by the current SKU
SKUEnvImpact	Total environmental impact of all decisions influenced by the current SKU
$SSVioDC_{i,dc,t}$	Amount of safety stock violation of SKU *i* in distribution center *dc* in week *t*
$SSVioWH_{i,w,t}$	Amount of safety stock violation of SKU *i* in warehouse *w* in week *t*
TotalCosts	Total costs of operating the supply chain
$TransDCR_{i,dc,r,t}$	Amount of SKU *i* transported from distribution center *dc* to retailer *r* in week *t*
$TransFW_{i,f,w,t}$	Amount of SKU *i* transported from factory *f* to warehouse *w* in week *t*
$TransIng_{h,s,f,t}$	Amount of ingredient *h* transported from supplier *s* to factory *f* in week *t*
$TransWDC_{i,w,dc,t}$	Amount of SKU *i* transported from warehouse *w* to distribution center *dc* in week *t*
γEI	Slack variable, represents the amount of environmental impact that exceeds the specified upper bound

γTC Slack variable, represents the amount of the total costs that exceeds the specified upper bound

8.1. [0-1] Variables (Can be treated as continuous)

$YFAMSU_{fam,f,t}$ Indicates if there is a set-up of SKU family *fam* in factory *f* in week *t*

8.2. Binary Variables

$WSU_{i,f,t}$ Binary variable indicating a set-up to SKU *i* at factory *f* in week *t*

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