Environmental Engineering and Management Journal April 2018, Vol.17, No. 4, 999-1007
http://www.eemj.icpm.tuiasi.ro/; http://www.eemj.eu

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COST-EFFECTIVENESS OF OPTIMIZING CONCENTRATED FEED BLENDS TO DECREASE GREENHOUSE GAS EMISSIONS

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Abstract

Livestock production is under growing public and scientific scrutiny for its greenhouse gas (GHG) emissions. This article contains a preliminary assessment of the inclusion of upstream life-cycle GHG emissions in concentrated feeds design, using the most common nonlinear programming optimization algorithms to determine feed composition. First, GHG emissions are included as costs in a single criteria optimization problem. The unit price of GHG emissions was obtained using a genetic algorithm. Second, GHG emissions are included as a target function to minimize in a multi criteria optimization problem using goal attainment programming. Results obtained after both optimization methods were applied to two case studies, namely fattening pigs and rabbit feeds. Changing ingredients in concentrated feed blends has a marginal effect on GHG emissions due to mandatory nutritional constraints. If the optimization is unconstrained, the maximum possible decrease in GHG emissions is 27.5% for the pigs feed, accompanied by increasing costs and a decrease in feed nutritional quality. To maintain nutritional integrity, the maximum possible reduction in GHG emissions is 7.5%. Considering cost as an optimization variable in the problem, the maximum decreases are even lower. It is possible to decrease emissions by 71% for the rabbits feed, but the cost of the reduction is higher than the opportunity cost for farmers to reduce GHG emissions using other strategies. These results are qualitatively robust but critically depend on feed ingredients GHG emissions and cost data.

Key words: genetic algorithm, goal programming, greenhouse gases, linear optimization, livestock feed

Received: May, 2013; Revised final: July, 2014; Accepted: July, 2014; Published in final edited form: April 2018

1. Introduction

Life Cycle Assessment (LCA) studies show that food and beverages are one of the three types of products with the largest environmental impacts in the European Union (Tukker et al., 2006). Meat production is particularly relevant for this score (Weidema et al., 2008). The contribution of the livestock sector to worldwide greenhouse gas (GHG) emissions is estimated in the range of 18% (Steinfeld et al., 2006) to 50% (Goodland and Anhang, 2010), although the upper estimate has been disputed (Herrero et al., 2011). Concentrated feed production (including sourcing of ingredients) and transportation are often the hotspots in meat production (Cederberg and Mattsson, 2000; Lewandowski et al., 1999; van der Werf et al., 2005). This means feeds formulations are the first place to look for optimization options.

Livestock feed formulation is usually treated as a programming optimization problem. One of the most widely used approaches is the least-cost feed formulation method using the simplex method to derive solutions of a linear programming model (Peng and Li, 2011). The model combines ingredients to obtain the optimum composition, which minimizes costs, subject to nutritional and ingredient availability constraints (Saxena et al., 2016). Several initiatives related to environmental product labeling are

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underway and will likely steer the market towards more environmentally-friendly meat products. In the future, producers may have to minimize environmental impacts as well as costs. The recent literature has thus been flourishing with authors trying to expand the typical feed optimization algorithms by including environmental criteria. Oishi et al. (2011) used the least-cost feed formulation method applied to the Japanese beef fattening system. They considered nitrogen (N) and phosphorus (P) as additional costs and introduced them in the least-cost objective function. Dubeau et al. (2011) approached the same problem in France and Québec by adding N and P as part of a multi-objective minimization problem (Žgajnar and Kavčič, 2009). The authors minimized N and P as objectives (objective functions) to quantify the trade-off between excretions and costs, providing a tool for decision-makers. They did not point out one specific optimum feed formula. If the objective is to find optima considering more than one function to minimize (or maximize: e.g. nutritional quality), problems regarding simultaneous attainment arise (Peric and Babic, 2009). If functions are minimized in parallel (equal weighs for all objectives), the final result may be neither optimum for any of them separately nor Pareto efficient. In optimizations that are not Pareto-efficient any improvement according to one criterion comes at the cost of another criterion.

To overcome this problem, Castrodeza et al. (2005) use a fractional model together with an Interactive Multiple Goal Programming (IMGP) decision method. With IMGP, each objective is optimized individually, and then the decision-maker, faced with the results, makes successive choices on which criteria to improve first, thus generating a second feasible solution space, and repeating the procedure until one solution remains. This method does not require the decision maker to know beforehand which goal is preferred, but it is not systematic and does not necessarily provide efficient results.

As an alternative, goal programming introduces preferences in problem formulations (Caballero et al., 2009). Farmers may have specific preferences that bias results towards their end. For example, Babic and Peric (2011) provide explicit goals for total feed cost, nutritional quality (share of nutrients) and water content, as well as several scenarios of farmer preference between criteria. Instead of relying on decision-maker *ad hoc* decisions, results can reflect the best feed formulation that respects optimization criteria in sequential order.

Using this framework, this article proposes methods to test the cost-effectiveness of decreasing upstream GHG emissions (i.e. considering life-cycle emissions for each feed ingredient) by replacing ingredients in feed blends. So far, the introduction of environmental variables in feed formulation problems has been restricted to N and P emissions or excretions (Finneran et al., 2010; Pomar et al., 2007) and methane (CH_4) emissions from etheric fermentation and manure management (Moraes et al., 2012). Moraes et al. (2012) tested the influence of a GHG tax in direct CH_4 emissions management, but the research question here is different: can life-cycle GHG emissions from feeds be reduced by changing feed ingredients while maintaining the same nutritional restrictions, and if so at what cost? By analyzing both emissions reduction and cost simultaneously, the feed cost increase per unit of GHG emissions reduction can be compared with international carbon market prices, thus determining the cost-effectiveness of the approach. The following section proposes two alternative methods to address this question, while the results section deals with the application of the methods to specific datasets.

2. Material and methods

2.1. Nonlinear programming method

The most generic formulation for the feed optimization problem is to minimize an objective function F (Eq. 1):

$$\min_X F(X) \tag{1}$$

where F is a function of vector $X = (x_1, x_2, \ldots, x_n)$ where x_j, $j = 1,\ldots,n$ denotes the proportion of ingredient j in the diet and n is the total number of ingredients available (Castrodeza et al., 2005). F is a vector of the t target functions to minimize or maximize (Eq. 2):

$$F(X) = \left(f_1(X), f_2(X), \ldots, f_t(X)\right)^T \tag{2}$$

Note that if there is only one criteria to optimize (e.g., cost), $F = f_1$. Essential nutritional requirements of animals (protein, energy, calcium, etc.) are not objective functions, but rather interval constraints on the minimum and maximum values x can take (Eq. 3):

$$\underline{b_i} \le \sum_{j=1}^{n} a_{i,j} x_j \le \overline{b_i} \tag{3}$$

where $i = 1, \ldots, k$. k is the number of nutrients (or constraints) considered, $a_{i,j}$ the amount of nutrient i in ingredient j, minimum and maximum b_i are the lower and upper bounds, respectively, of nutrient i in the diet. There may also be lower or upper thresholds for the amount of some ingredients in the feed. Considering s_j is the maximum proportion of ingredient j in the diet, the case where there is a maximum amount is translated by Eq. (4):

$$x_j \le s_j \tag{4}$$

Two methodological possibilities were tested to introduce GHG emissions as an optimization parameter: (a) following Oishi et al. (2011), consider GHG as an additional cost in a single criterion optimization problem, as described in section 2.2

below; (b) following Babic and Peric (2011), consider GHG an additional target function, and apply goal attainment programming, as explained in section 2.3.

2.2. GHG emissions as part of least-cost optimization

In the least-cost optimization, Eq. (2) becomes (Castrodeza et al., 2005) (Eq. 5):

$$F(X) = f_1(X) = \sum_{j=1}^{n} c_j x_j \tag{5}$$

where c_j is the unit cost of ingredient j. Considering GHG emissions as an additional cost (Oishi et al., 2011), Eq. (5) becomes (Eq. 6):

$$F(X) = \sum_{j=1}^{n} \left(p_j + \beta \cdot GHG_j\right) x_j \tag{6}$$

where p_j is the unit price (i.e. per unit of mass) of ingredient j, GHG_j is the unit CO_2e emissions of ingredient j, and β is the cost of each unit of CO_2e emitted. β is calculated as the increase in feed cost needed for a given decrease in total emissions.

Eq. (6) can only be minimized as a single criteria optimization problem if β is known. There are two possible ways to estimate β. First, it could be introduced as an exogenous variable, in which case it would be the average cost of GHG emissions obtained from some external source. This is the approach followed by Oishi et al. (2011). The social cost of carbon and the international carbon market price are examples of external sources that could potentially be used. Alternative, it is possible to find β using the same datasets that are also employed in the optimization step. Since the meaning of β is narrower as it applies only to the price of carbon emitter due to feed blends ingredients, in this work the second strategy was chosen, using a genetic algorithm (GA). GA finds a Pareto-efficient solution space (Sahman et al., 2009) where both variables - cost and GHG emissions - are minimized simultaneously (Eq. 7):

$$\begin{cases} f_1(X) = \sum_{j=1}^{n} p_j x_j \\ f_2(X) = \sum_{j=1}^{n} GHG_j x_j \end{cases} \tag{7}$$

Both equations are optimized considering nutritional constraints. The result of the GA application is not one optimum feed mix that minimizes both simultaneously, but rather an “efficiency frontier” depicted by a curve whose points are all Pareto-efficient combinations. Eq. (7) is thus not an optimization problem since it does not yield a unique solution. Its objective is only to find β and use the parameter in Eq. (6).

2.3. Multi criteria optimization with goal attainments

Alternatively to the process described in section 2.2, where a single target function is optimized, multi criteria optimization can also be performed using multiple target functions as depicted by Eq. (2). Multiple goal attainment requires *a priori* ranking between objectives. The objective is to minimize the deviations from the target function’s goals. Former objective functions are thus modified and become additional restrictions in the problem (Babic and Peric, 2011) (Eq. 8):

$$f_t(X) - w_t \gamma_t = G_t \tag{8}$$

and each function t is evaluated with vector solution X, minus the deviation γ weighed with the decision makers’ preference parameter w has to be equal to the goal G. Note that γ can be positive or negative (a negative deviation is an overshoot).

2.4. Data for case study comparisons

The methods in sections 2.2 and 2.3 were primarily applied to a case study feed for fattening pigs, as described by Babic and Peric (2011). Originally three criteria were optimized – water content, nutritional quality and cost of each ingredient in a pig growth feed, including nutritional and ingredient availability restrictions. The entire dataset can be found in the original paper. Babic and Peric (2011) assign dual role to nutritional requirements: they are constraints as well as an optimization goal. First, minimum or maximum nutritional restrictions are included for raw protein, pulp, calcium, phosphorus, ash, methionine, lysine, tryptophan, threonine, isoleucine, histidine, valine, leucine, arginine and phenylalanine. These restrictions ensure that the necessary dose of each ingredient is included in every feed. The amount of each nutrient in the feed is included as a fraction of the total amount needed to ensure maximum growth. Additionally, the sum of all nutrient fractions is itself a maximization goal to ensure weight gain. This means that feeds that contain high digestibility ingredients are favored. The present article also assumes this dual role of nutrition for the multi criteria optimization problem. For least-cost optimization, nutrition is only included as a constraint. Also similarly to Babic and Peric (2011), in this article ingredients add up to 97% of the mass of the feed. The additional 3% mass respects to minor ingredients and additives that must be part of the feed and cannot be optimized.

Data on GHG emissions of the ingredients was obtained as an average of all records of a similar type in the Carbonostics (www.carbonostics.com) proprietary database, adapted from results presented in Teixeira (2014). Carbonostics is an LCA tool specialized on the agri-food sector. Note that GHG emissions are the only LCA environmental indicator used due to data availability and also to maintain a minimum possible level of complexity (less parameters to optimize). Plus, this dataset considers the emissions up until the end of production of the ingredients of the feed. Emissions from the digestion of the feed and manure are not included (Table 1).

Table 1. Data on life cycle GHG emissions from the ingredients considered

Ingredient	*GHG[a] Emissions (kg CO_2e/kg)*
Barley	0.54
Maize	0.27
Lucerne	0.24
Powdered milk	9.11
Fish meal	1.60
Soya	0.68
Soya hulls	0.52
Dried whey	0.08
Rapepellets	0.30
Wheat	0.47
Rye	0.42
Millet	0.47
Sunflower pellets	0.13

[a]GHG – Greenhouse gases. Source: adapted from the database used in Teixeira (2014)

For goal attainment, Babic and Peric (2011) indicate as goals for cost 1.85 monetary units (MU), for the share of nutrients 77%, and for the share of water 8.3%. This paper introduces a further objective for GHG emissions of 0 kg CO_2e. While zero emissions are an impossible target, it is the simplest number that guarantees the maximum priority for the goal of emissions reduction. Any number minor or equal than the minimum feasible solution for emissions provides the same result. Also, Babic and Peric (2011) test four scenarios (A-D), to which three more (E-G) are added, according to Table 2. To have a higher priority means to have the highest weight (w_t in Eq. (8)).

The GA, linear optimization and goal attainment methods were applied using the software MATLAB 7, using the functions “gamultiobj”, “fmincom” and “fgoalattain”, respectively.

After examining data from Babic and Peric (2011), the same method was applied to datasets from two other research articles. The first one, Castrodeza et al. (2005), also targets growing pigs, but has a wider range of ingredients and different nutritional constraints since one of the goals of the work is to limit nitrogen pollution as ensured by a balanced pig diet. In this case the nutritional criteria are crude fiber, methionine plus cysteine, tryptophan, threonine, calcium, total phosphorus, available phosphorus, dry matter, crude protein, lysine, and digestible energy. The second dataset, Altun and Sahman (2013), focused on feeds for rabbits. The nutritional criteria are similar to Castrodeza et al. (2005). Furthermore, while Babic and Petric (2011) use unknown monetary units, Castrodeza et al. (2005) use Euros and Altun and Sahman (2013) use Turkish Liras.

3. Results and discussion

3.1. Application of the genetic algorithm

Application of the GA provided the Pareto frontier defined by the solutions depicted in Fig 1. The frontier can be depicted, in the simplest case, by a linear relation (R^2=86.9%). A better fit is obtained when the curve is depicted as a second-order polynomial (R^2=94.2%). In either case, the figure shows that increasing costs from 2.34 to 2.36 MU results in a significant decrease of GHG emissions (0.55 to 0.49 kg CO_2e). To further decrease emissions results in heavily increasing costs. Parameter β, the marginal cost of abating GHG emissions in feeds, is calculated the two possible fits in Fig. 1.

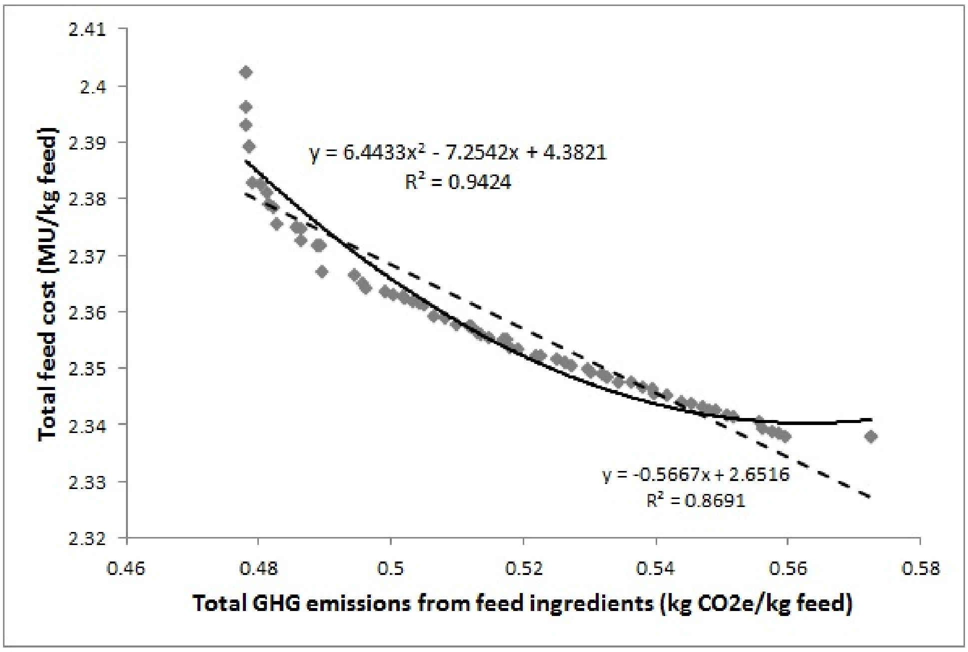

Fig. 1. Pareto frontier for the multi-objective optimization problem of minimizing feed cost and GHG emissions, using a genetic algorithm (MU – Monetary units)

Table 2. Objectives for the goal attainment problem

Scenario		***A***	***B***	***C***	***D***	***E***	***F***	***G***
Priority is to minimize:	1st	Exceeding costs	Nutrient shortfall	Water excess	Exceeding costs & Exceeding raw protein	GHG emissions	GHG emissions	GHG emissions &Nutrient shortfall
	2nd	Nutrient shortfall	Exceeding costs	Exceeding costs	Nutrient shortfall	Exceeding costs	-	-
	3rd	Water excess	Water excess	Nutrient shortfall	Water excess	Nutrient shortfall	-	-
	4th	-	-	-	-	Water excess	-	-

Using the linear expression (Eq. 9):

$$\beta_{linear} = -\frac{dC}{dCO_2e} = 0.5667 \tag{9}$$

The consequence of the linear factor is that the contribution of GHG emissions cost to the minimization function is always negative, i.e., to decrease emissions farmers must increase costs. Using the quadratic expression (Eq. 10):

$$\beta_{quad} = -\frac{dC}{dCO_2e} = -12.8866 \cdot CO_2e + 7.2542 \tag{10}$$

This approach makes the marginal effect dependent on the level of GHG emissions. It interprets the curve as making trade-offs otherwise hard to capture for very low or very high CO_2e emissions, which is where the curve in Fig. 1 is not linear. In Eq. (10), the role of GHG emissions in the minimization function is positive or negative depending on the ingredient. Ingredients with low cost and emissions have a positive contribution, i.e., increasing their share in the feed is a double positive contribution to cost minimization. This quadratic β estimation is thus qualitatively preferable to the linear approach, but quantitative differences in final results only arise when there is a large share of fringe (in terms of emissions) ingredients. The next section shows that this is never the case in the datasets used in this work.

3.2. GHG emissions as part of least-cost optimization

There are two options for replacing β in the Eq. (6) target function (Eqs. 11-12):

$$\min_x \left(p_i + 0.5667 \cdot CO_2e\right)x_i \tag{11}$$

$$\min_x \left(p_i + 12.8866 \cdot CO_2e^2 - 7.2542 \cdot CO_2e\right)x_i \tag{12}$$

Eqs. (11) and (12) are dimensionally correct optimization problems. There is no trade-off between cost and GHG emissions because the solution of the optimization problem is already the most efficient (the one that minimizes cost and GHG emissions), by definition of β. The application of the LP algorithm yields results shown in Table 3, which shows that the feed obtained for cost minimization without including GHG emissions in the objective function has the highest GHG and lowest cost. Results vary depending on whether GHG costs change linearly or quadratically with ingredient cost. In the first case, the cost of reducing each kg CO_2e is 0.407 MU; the maximum reduction in GHG emissions that satisfies nutritional constraints is 3.1%. In the second case, the cost is 2.713 MU/kgCO_2e, and the maximum reduction in GHG emissions is 7.5%.

The high cost has to do with the strict restriction that all trade-offs during the application of the GA must be Pareto-optimal. The main differences in feed formulation is a shift towards the replacement of barley with soya hulls and rye, which are more efficient in terms of the balance nutrition/CO_2e emissions but also more expensive.

Table 3. Results of inserting GHG emission costs in the objective cost function to minimize

Ingredient/ Indicator	***Only feed costs***	***Linear GHG, Eq. (11)***	***Quadratic GHG, Eq. (12)***
Barley (%[a])	0.15	0.06	0.09
Maize (%)	0.15	0.15	0.15
Lucerne (%)	0.03	0.04	0.03
Powdered milk (%)	0	0	0
Fish meal (%)	0	0	0
Soya (%)	0.12	0.12	0
Soya hulls (%)	0	0	0.11
Dried whey (%)	0	0	0
Rapepellets (%)	0.15	0.15	0.15
Wheat (%)	0.15	0.15	0.15
Rye (%)	0.07	0.15	0.15
Millet (%)	0	0	0
Sunflower pellets (%)	0.15	0.15	0.15
GHG[b] emissions (kg CO_2e/kg feed)	**0.377**	**0.365**	**0.349**
Cost (MU/kg feed[c])	**1.836**	**1.841**	**1.913**
Nutrients (per kg feed)	71.898	71.983	70.562
Water (per kg feed)	9.721	9.713	9.871

[a] The sum of all percentages is 97% because the additional 3% are minor ingredients and additives set aside from the optimization;
[b] GHG – Greenhouse gases; [c] MU – Monetary Units

3.3. Multi criteria optimization with goal attainments

Results are shown in Table 4. Scenario A, which is a cost-first optimization, is comparable to the previous cost minimization approach. Results from Scenario A are similar to those in Table 3, indicating some mutual reinforcement of the two approaches.

The cost of reducing each unit of CO_2e in other scenarios is higher than in Scenario A: 7.7 MU for Scenario E, 10.9 MU for Scenario F and 47.5 MU for Scenario G. The relative decreases in GHG emissions are 19.1%, 27.5% and 7.5%, respectively. Feed quality always drops when GHG emissions decrease, and water consumption also seems to decrease with GHG emissions. Regarding feed formulations, in this case barley, powdered milk and fish meal are removed from the feed, and in Scenario F wheat is also reduced to a third. In Scenario G, in which GHG emissions reduction and maintaining feed quality are equally important, the decrease in GHG emissions is much lower than in Scenario F, but total nutrition is similar to Scenario B. This means that it is possible to reduce GHG emissions while maintaining quality standards, but at the expense of a 73.4% increase in costs. Results are shown in Table 4.

3.4. Application to other data sets and animal types

Data from Castrodeza et al. (2005) was analyzed using multi-objective goal attainment using two possible objectives: cost minimization and GHG emissions minimization. While weights may vary, there are only two feasible solutions, which correspond to cost-first and GHG reduction-first. It is possible to reduce GHG emissions by 18.5%, with a cost of 12.87 €/t feed. This means that the reduction of each ton of CO_2e costs 135.34 €.

Evaluating data from Altun and Sahman (2013) under multi-objective goal attainment also provides two feasible solutions only (cost-first and GHG reduction-first). This is when the highest improvement potential surfaces. Switching from Scenario A to B would decrease emissions by 73%, while increasing costs by 4.73 Krs/kg feed. This means that, under this method, the cost of reducing emissions is 5.09 Krs/kg CO_2e, or, at the conversion rate of 1 Krs = 0.44 cents of €, 22.38 €/ t CO_2e.

3.5. Economic efficiency of replacing feed ingredients

Cost minimization results, in the case when GHG emissions are introduced as extra costs, produced a strict constraint on feed blend that required solutions to be Pareto-efficient. As a consequence, smaller reductions in GHG emissions are obtainable. A higher potential for decrease was obtained only when using multi objective optimization. Since this procedure does not discard Pareto-dominated solutions, it is possible to decrease GHG emissions more than with the GA cost minimization method, but also at much higher costs. The two methods are indeed convergent in comparable situations, i.e. when costs are the main variable to minimize. Multiple goal attainment should be used preferably when there is flexibility for more drastic (but ultimately constrained) changes in production. Results cast doubt over the cost-efficiency of switching ingredients in a feed to decrease its life-cycle emissions. Let us consider that the maximum opportunity cost for farmers is the reference cost for GHG emissions in the international carbon market (20 €/t CO_2e). It is possible that some farmers find even lower costs with other GHG minimization strategies (carbon sequestration in soils, change of tillage method etc.). For the rabbits feed, the result is similar to the reference cost (22.38 €/ t CO_2e), but for pigs feed it is much higher (135.34 €). Considering that the cost found for rabbits feed corresponds to a decrease in 71% in emissions, which is the maximum possible reduction considering the constraints, it is highly doubtful that a blend that uses different ingredients can be even more efficient, and thus more cost-effective in reducing emissions.

Table 4. Results of the application of the goal attainment algorithm to data from Babic and Petric (2011)

Ingredient/Indicator	***Scenario***						
	A	***B***	***C***	***D***	***E***	***F***	***G***
Barley (%[a])	0.13	0.04	0.07	0.15	0	0	0
Maize (%)	0.15	0.15	0	0.15	0.15	0.15	0.15
Lucerne (%)	0	0	0.64	0	0	0.06	0
Powdered milk (%)	0	0.07	0.08	0.10	0	0	0
Fish meal (%)	0	0	0	0.02	0	0	0
Soya (%)	0.13	0.15	0.15	0	0.10	0	0.15
Soya hulls (%)	0	0.15	0	0.02	0.02	0.11	0.15
Dried whey (%)	0	0	0.15	0	0.15	0.15	0.15
Rapepellets (%)	0.15	0	0.15	0	0.15	0.15	0
Wheat (%)	0.15	0.15	0	0.15	0.15	0.05	0.15
Rye (%)	0.11	0.15	0.15	0.08	0.10	0.15	0.07
Millet (%)	0	0	0	0.15	0	0	0
Sunflower pellets (%)	0.15	0.11	0.15	0.15	0.15	0.15	0.15
GHG[b] emissions (kg CO_2e/kg feed)	**0.381**	**1.004**	**1.194**	**1.261**	**0.308**	**0.276**	**0.353**
Cost (MU/kg feed[c])	**1.850**	**2.409**	**3.299**	**2.580**	**2.410**	**2.996**	**3.208**
Nutrients (per kg feed)	73.291	77.000	71.151	71.849	73.916	69.808	76.647
Water (per kg feed)	9.834	10.255	8.300	9.955	9.111	8.906	9.498

[a] The sum of all percentages is 97% because the additional 3% are minor ingredients and additives set aside from the optimization; [b] GHG – Greenhouse gases; [c] MU – Monetary Units

Changes in pigs and rabbits feed blends can be considered a mildly cost-effective policy because it stands mid-range in estimates of cost-effectiveness of policies for GHG emissions mitigation. For example, in France for the year 2030, the cost-effectiveness of measures in the agricultural sector for GHG mitigation ranges from approximately negative 440€ to positive 460€ for each ton of CO_2e averted (the negative estimate meaning a cost and the positive revenue) (Pellerin et al., 2013). In the UK, there are measures for GHG mitigation that cost as much as 1750 British pounds per ton of CO_2e, and others that have a positive result of 300 pounds (Moran et al., 2011). In Ireland, the range is between minus 600 and 300€/ t CO_2e (Schulte et al., 2012). One of the measures indicated for France whose cost is similar to those obtained above for the optimization of these particular feed blends is to reduce the amount of protein in the diet of livestock to limit the quantity of nitrogen excreted in manure and the associated N_2O emissions (Pellerin et al., 2013). The similarity of the cost-effectiveness of the measure and the calculations in this work is an important source of validation for these results. Measures that are based on efficiency improvements, such as feed blend optimization, are typically more expensive than others based on land use change and technological innovation (Schulte et al., 2012).

In the future, the inclusion of GHG emissions can be tested in other feed optimization algorithms, like for example different variants of the Particle Swarm Optimization (PSO) method. Altun and Sahman (2013) applied PSO to cost minimization of rabbit feeds, and found that PSO is more efficient at computing stable optimum values than GA. However, the present article found remarkably similar results for rabbit feeds using multi-objective goal optimization: 25.34 Krs/kg feed for cost minimization and 30.08 krs/kg for GHG emissions minimization (against 26.73 and 30.17 Krs/kg feed for ingredients that minimize cost and ingredients that do not, obtained using PSO in the original Altun and Sahman (2013) article).

Introducing other objective functions (such as GHG emissions) to minimize in PSO requires multi-objective PSO (MOPSO) (Coello et al., 2004). MOPSO has been applied for the first time in fish feed design by Zhang and Wang (2010). The authors identify advantages in this method but ran into practical problems regarding convergence of solutions if running time is longer or if cost and nutritional goals are in conflict, despite having disregarded complex nutrient interactions. The optimum formulas found with MOPSO rely heavily on by-products, which have low GHG emissions if impacts are allocated economically, but also include fish meal which has high emissions (Zhang and Wang, 2010). The inclusion of a GHG reduction goal would thus provide more conflicting results, at least until preferences are included in the MOPSO objective functions (Mostaghim, 2010). All in all, MOPSO is more robust than GA but the results can be very similar, since both consider only Pareto efficient solutions. This means that MOPSO models will likely not find other optimum solutions that minimize GHG emissions beyond the limits found in this work.

3.6. Limitations and future work

The present work is limited in scope to the analysis of directly replacing feedstocks in particular concentrated feed blends. The next step is to compare the potential for GHG reductions by replacing part of the feed with grazing. Another option is to test more ingredients and blends, since other ingredients may produce more drastic results. In fact, some minor ingredients (but nutritionally crucial) were ignored due to their residual contribution to the overall weight of the feed (and thus also to its life-cycle emissions). It is also relevant in the future to connect this work and the work by Moraes et al. (2012), because changing feed formulations also has an impact in its digestion by animals and ensuing enteric emissions and emissions from manure. Ideally, direct and life cycle emissions should be considered simultaneously. Digestion of feeds was not included in this analysis, only life-cycle emissions from feed ingredient production.

To minimize uncertainty from using secondary GHG emissions databases, it is preferable to perform a full LCA of the feed ingredients rather than rely on average GHG emissions as those presented in Table 1 when these methods are applied to optimize actual feeds. Despite the methodological consistency and relatively low uncertainty of these averages (Teixeira, 2014), there are different methodological choices that could provide different results (e.g. using consequential rather than attributional LCA). Despite the fact that this article does not include a quantitative analysis of uncertainty it is clear that results are crucially dependent on GHG emissions data, as well as the highly volatile feed ingredients prices.

Also regarding uncertainty, the convergence shown in the previous section between results obtained using both approaches in this article and other studies provides some degree of confidence in the robustness of the conclusions. For example, the GA used in the least-cost approach could have been replaced by other estimates for the price of carbon. This methodological choice is a source of uncertainty. Multi criteria optimization, however, does not require an explicit cost of GHG emissions in monetary units and still arrives at similar results in equivalent scenarios. In conclusion, it is plausible to assume high quantitative uncertainty in the results presented here and in similar studies but qualitatively the conclusions are robust.

Further datasets should also be explored. In this work pigs and rabbits feeds displayed different potential GHG emissions reduction estimates; this does not, however, translate into a general higher GHG reduction potential in rabbit production rather than pig. Results presented here are explained simply by differences in ingredients used in these particular datasets. Since some ingredients with high or low GHG emissions are more common in feeds for rabbits or pigs, it may be the case that the potential for amelioration does depend on animal type – but this conclusion can only be drawn after more comprehensive datasets are explored.

Finally, since being able to pinpoint where in the life cycle of the production of the feed is more efficient to reduce emissions is of the utmost importance, the cost-effectiveness of improving feedstock production should be determined and compared with the results of this work. If it proves to be less costly to improve each crop's production than to change feed formulations, then that should be the target of farmers efforts.

4. Conclusions

Changing concentrated feed blends has a marginal effect on CO_2e emissions due to tight nutritional and cost constraints. For the pigs feed studied, the maximum possible decrease in GHG emissions is 27.5%; ensuring nutritional integrity, the maximum possible reduction in GHG emissions is 7.5%. In rabbits feeds emissions could be decreased by 71%, but at a cost that would exceed the opportunity cost for farmers to reduce emissions elsewhere.

Changing feeds to mitigate GHG emissions is at best mildly cost-effective, but it cannot be discarded since any improvements will affect 825 million tons of feeds produced each year (Feed International, 2014).

Acknowledgements

This work was partially supported by the European Commission's 7th Framework Programme through Marie Curie Intra-European Fellowship for Career Development number 331896 for Project "Bio-LCA: Introducing biodiversity in Life Cycle Assessment (LCA)", and by grant SFRH/BPD/111730/2015 from Fundação para a Ciência e Tecnologia. The author thanks Sara Pax for kindly granting access to the Carbonostics database and two anonymous referees who provided important comments on earlier versions of this article.

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