

Use of livestock quality estimates for improved product allocation planning to meat processing locations

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Abstract

Individual farmers have different production and rearing systems, which lead to differences in quality features of their animals (such as carcass weight and lean meat percentage). We consider the case of a large European meat processor that currently does not use available information on these quality differences to allocate farm deliveries to processing locations; current farmer allocation is aimed at minimizing transport costs. However, due to specific market requirements or processing options, different quality features result in different product yields in different processing locations. This research assesses the value of using quality information in supply planning of meat processors and analyzes the impact of this strategy on transport costs and product yield. We developed a MILP model to compare a quality-based allocation strategy with the current allocation strategy. Case results revealed that the new strategy could improve the net value of an allocation plan significantly with an increase of 1.5%. Sensitivity analyses show that transport costs and location specific product yield of different product qualities affect this improvement. However, even for increases / decreases of up to 300 % for these inputs, the new strategy remains considerably advantageous. These results indicate that the use of quality information in supply planning is likely to have a strong impact on the overall livestock yield at multi-location meat processing companies.

1. Introduction

Many food processors claim that consumer demand has become more difficult to understand and predict, especially in the developed world. Grunert (2006) states that this complexity stems from the increasing heterogeneity in consumer demand. This author also points out that this complexity creates new opportunities for food processors to add value by differentiating production. Differentiation in consumer demand for food is related to taste, ease of use (convenience), and production process characteristics (e.g. slaughtering method or sustainability), and it creates different customer segments (Brunso et al., 2002). To serve these customer segments, consumer demand must be translated into useful specifications for different chain actors (Perez, de Castro, 2009). Recent research has indicated that using more advanced product quality information in logistics decision making can improve market performance (Van der Vorst et al., 2009). This advanced information can be used in a supply chain optimisation to steer products to those market segments that value their specific product characteristics most, and links up to the Quality Controlled Logistics framework suggested by the same author.

This research will focus on the use of product quality information in supply planning of meat processing companies. Differences in production and rearing systems of farmers lead to variation in animal quality features such as carcass weight, fat layer thickness, and lean meat percentage. Current practice is to determine these quality features after slaughtering and to use this information to group carcasses into different quality classes. These classes are used in logistics decision making for further processing and to determine carcass value (Boland et al., 1995). In processing companies with multiple processing locations a lack of specific processing equipment in some locations or differences in handling procedures results in restricted access to some market segments. This restricted access could limit the match between quality features of supplied livestock and those required by the target markets. This

mismatch may lead to sub-optimal production planning and reduced product yields. A clarifying example is given in the following text box.

A beef carcass with quality features F is most valuable if sold to customer C. This customer, however, demands that pig meat and beef are not processed at the same location. Pig meat processing is done at slaughterhouse S. Therefore transporting cattle to slaughterhouse S implies that these animal products cannot be sold to customer C anymore. Delivering cattle with quality features F to slaughterhouse S will thus result in a loss of potential value.

This example merely illustrates how supply allocation might affect product yield. There is a variety of operational constraints that prevent product access from production facilities to target markets (e.g. restrictions on quality systems, animal types processed), whereas target markets have different preferences for quality features (e.g. Asia prefers fat meat products, Greece prefers light and lean carcasses), which results in different values of one carcass class at different markets. These combined effects lead to differences in values for different carcass classes at different locations.

The large European meat processing company we consider in this case study does not use information on meat quality that individual farmers deliver in supply planning; it simply transports animals to the nearest processing location to minimize transport costs. By doing so, the inherent variation in quality between animals of different farmers is not exploited to match supplied and demanded quality features at processing locations. This results in losses of potential value. However, allocating batches of livestock to processing plants using quality information might reduce these losses. Quality information could improve the location specific match between supplied quality features of livestock and the demanded final product quality. This, however, would also result in higher transportation costs since the livestock would no longer be transported to the nearest processor. This research assesses the value of using quality information in supply planning of a meat processor. It will also analyze how this strategy impacts transport costs and product yield. Our research was conducted with real life data. However, due to confidentiality reasons, we will present a simplified model as a proof of concept.

The article is structured into eight sections. It starts with a description of the problem and an overview of our modeling assumptions, along with a small motivating example (section 2). This is followed by a description of the Mixed Integer Linear Programming (MILP) model used in solving our case study (section 3). In the experimental section, the case study is introduced and solved with the use of the proposed MILP model (section 4). After the experimental section, we give an overview of our results (section 4.1). This is followed by a section in which the sensitivity of the model for the two most important inputs is analyzed (section 4.2). The final two sections present a discussion of the results and potential future directions for research (section 5), and the conclusions drawn (section 6).

2. Problem description

The large European meat processing company we consider in this case study owns multiple processing locations. Each day this company buys livestock batches from a large, fixed group of farmers and then transports these batches from the farmers to meat processing locations. The company currently transport the livestock batches from a farm to the nearest processing location to minimize transport costs, which are paid by the processing company itself. After

slaughtering, information on a variety of carcass quality features (e.g. weight, lean meat ratio) is gathered by measurements. This quality information is used to divide carcasses into different quality classes. These classes are then used to match supplied with demanded quality features and to determine the price a farmer gets for his animals. The method of carcass grading and the price a farmer gets for his animals is independent of the processing location.

In this paper, we compare the current strategy of using post-slaughter quality information with a strategy of using percentage estimates of animals that a farmer delivers in a certain quality class to meat processors. We begin by describing the supply network consisting of I farms (identified by index i), J processing locations (identified by index j) and K carcass quality classes (identified by index k). This description will be followed by a small scale example to demonstrate the network's main allocation principles.

In the supply network each farmer i delivers a determined number of animals, a_i . a_i is known in a real-life situation, since farmers have to indicate the number of animals they will supply two weeks in advance. We consider different scenarios for the quality a farmer will deliver, in which each scenario represents an option for the percentage of animals a farmer will deliver in a certain quality class in a future delivery. We represent the quality distribution delivered by a specific farmer by a discrete multivariate random variable (i.e. a random vector) q_{ikl} . q_{ikl} denotes the percentage of animals that farmer i will deliver in carcass quality k under scenario l . L scenarios (identified through index l) are considered to represent the probability distribution of the animal quality delivered by a farmer, and the variable m_{il} denotes the probability that scenario l occurs for farmer i . Both the percentage of animals delivered by a farmer in a class for a given scenario (q_{ikl}) and the probability of these scenarios (m_{il}) can be derived from historical delivery data that is available to the meat processor using statistical analysis.

Each meat processing location has a maximum number of animals it can process due to limited availability of processing equipment and labor. The maximum capacity of processing location j is denoted as c_j . A potential value of a carcass of quality class k that is processed at location j is denoted by p_{jk} . This value is measured in € per carcass.

The costs for transporting one animal from farm i to processing location j is defined by d_{ij} . This value is measured in € per transported animal, and incorporates only variable, distance-dependent costs. Costs for loading and unloading of livestock, veterinary inspection, etc. are excluded since they do not differ across farmers and processing locations.

In the processing network, the decision maker is interested in how to allocate livestock batches to his processing locations. This allocation is represented in the network by a binary decision variable X_{ij} . X_{ij} represents a transport of all available animals at farm i to processing location j .

To motivate the description given above a small scale example is described to show the principles of the logic that we apply in this study, and to clarify the allocation strategies.

2.1. A simplified example

Figure 1 gives an overview of a simplified supply network. The farmer characteristics used in this example are based on real data and are as follows: quality estimates (q_{ikl}), number of animals farmers will deliver (a_i), and transport costs of animals to processors (d_{ij}). The

processing capacity (c_j) and the product yield of carcass qualities at the different processing locations (p_{jk}) were chosen so as to fit the example.

This network consists of four farms $\{i=1,2,3,4\}$, two processing locations $\{j=1,2\}$ and a total number of eight ($i * j = 2 * 4$) binary decision variables $\{X_{11}, X_{12}, X_{21}, X_{22}, X_{31}, X_{32}, X_{41}, X_{42}\}$ that connect farms with processing locations.

The farmers deliver livestock batches with the following sizes $\{a_1 = 72, a_2 = 80, a_3 = 102, a_4 = 83\}$. Two carcass quality classes are considered in this example $\{k = 1,2\}$. For the first carcass class, we will use location-specific product yield, and for the second class, we will assume that product yield does not differ between processing locations. The estimates of the considered carcass classes are represented by a probability mass function for each farmer with two different scenarios $\{l = 1,2\}$. A scenario represents a percentage of animals a farmer will deliver in a certain quality class in a future delivery. These percentages are derived from historical data. The ratios that were used for the quality estimates for quality class 1 for both scenarios are as follows: $\{q_{111} = 36\%, q_{112} = 20\%, q_{211} = 35\%, q_{212} = 35\%, q_{311} = 43\%, q_{312} = 25\%, q_{411} = 28\%, q_{412} = 20\%\}$; and consequently for the second quality class $\{q_{121} = 64\%, q_{122} = 80\%, q_{221} = 65\%, q_{222} = 65\%, q_{321} = 57\%, q_{322} = 75\%, q_{421} = 72\%, q_{422} = 80\%\}$. In this example $q_{111} = 36\%$ and $q_{121} = 64\%$, mean that under scenario 1 36 % of the animals delivered by farmer 1 will be classified into quality class 1, whereas the other 64 % will be in quality class 2. We assume the following scenario probabilities: $\{m_{11} = 50\%, m_{12} = 50\%, m_{21} = 50\%, m_{22} = 50\%, m_{31} = 50\%, m_{32} = 50\%, m_{41} = 50\%, m_{42} = 50\%\}$.

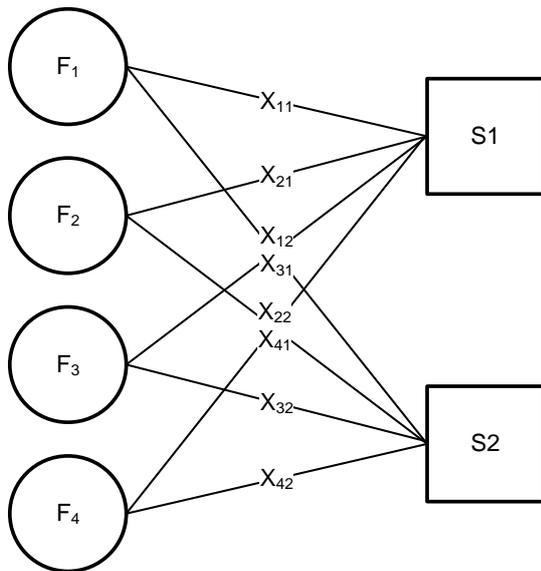


Figure 1 Schematic overview of motivating example

In our running example maximum processing capacities of $\{c_1 = 200, c_2 = 200\}$ for the processing locations are used. These capacities are unrealistic for a meat processor and are merely used for convenience in our small-scale example. For each carcass at processing locations in quality class 1 and 2 we assume the following product yields, $\{p_{11} = \text{€ } 120, p_{21} = \text{€ } 87, p_{12} = \text{€ } 75, p_{22} = \text{€ } 75\}$. In this running example transport costs are calculated by multiplying transport distances of the 4 farmers by an average transport cost derived from Baltussen et al. (2010). The resulting costs for transporting one animal from the farm to the processing location are $\{d_{11} = \text{€ } 0.60, d_{12} = \text{€ } 1.46, d_{21} = \text{€ } 0.40, d_{22} = \text{€ } 0.49, d_{31} = \text{€ } 1.11, d_{32} = \text{€ } 0.88, d_{41} = \text{€ } 1.40, d_{42} = \text{€ } 1.18\}$.

This completes our motivating example. We will now describe the constraints required in this network allocation problem, and introduce the mathematical models used to come to allocation plans.

Allocation plans must satisfy two constraints. The first constraint prevents the allocation plan from exceeding the maximum capacity of the processing locations:

$$\text{for all } j \quad \sum_i X_{ij} a_i \leq c_j \quad (1)$$

The second constraint ensures that all batches of livestock are allocated to a single processing location:

$$\text{for all } i \quad \sum_j X_{ij} = 1 \quad (2)$$

This is a realistic constraint since livestock batches are transported in complete truck-loads to processors. Furthermore, separating livestock on the farm based on quality features is considered infeasible, since no cost-effective techniques to estimate livestock quality features with reasonable accuracy is available.

The performance of allocation plans is based on the *net value* of an allocation plan. This *net value* consists of two parts: *gross yield* and *transport costs*.

The gross yield (Formula 3) is computed based on the quality and location dependent product yield of all allocated carcasses. It is calculated by multiplying the number of allocated animal batches (X_{ij}), by the number of animals in the livestock batch (a_i), by the product yield of the carcass classes at this location (p_{jk}), by the percentage of animals a farmer delivers in quality class k and scenario l (q_{ikl}), and by the likelihood of the different scenarios (m_{il}). The mathematical formulation of gross yield $E(Y)$ in € is as follows

$$E(Y) = \sum_i \sum_j \sum_k \sum_l \{X_{ij} \times a_i \times p_{jk} \times q_{ikl} \times m_{il}\} \quad (3)$$

The transportation of animals from farms to processing locations result in transportation costs. These costs are calculated by multiplying the allocated animal batches (X_{ij}) by the number of animals in the livestock batch (a_i), and by transport costs (d_{ij}) in € per animal. The mathematical formulation of transport costs $E(T)$ in € is as follows

$$E(T) = \sum_i \sum_j X_{ij} \times a_i \times d_{ij} \quad (4)$$

By combining the *gross yield* $E(Y)$ and *transport costs* $E(T)$, we can calculate what we call the *net value* $E(NV)$ of an allocation plan as

$$E(NV) = E(Y) - E(T) \quad (5)$$

The *net value* is also measured in €.

The following paragraphs describe two allocation strategies with their objective functions, and present the resulting allocation plan for our small running example. Afterwards, an

overview of the impact of allocation strategies on gross yield $E(Y)$, transport costs $E(T)$, and net value $E(NV)$ of our running example is given.

Plan 1: minimization of transport costs

This supply strategy reflects the current planning that aims to minimize transport costs. The objective function can be defined as

$$\min \{E(T)\}. \tag{6}$$

The corresponding optimal allocation plan is depicted in Figure 2.

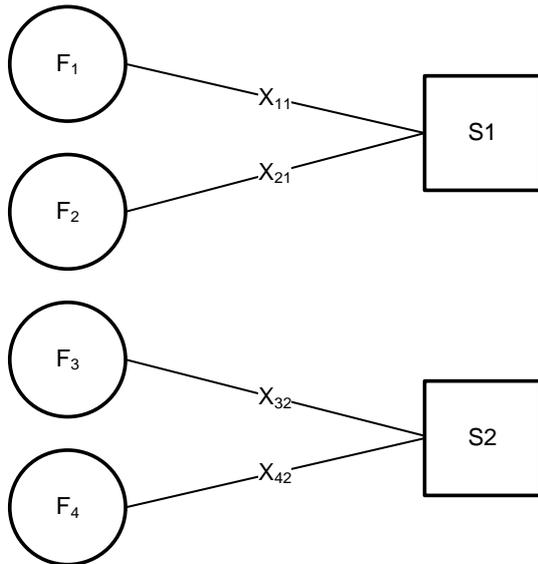


Figure 2 Example of allocation based on minimized transport costs

A performance overview of this allocation plan is given at the end of this section, where a comparison with the quality-based allocation strategy is discussed.

Plan 2: optimized net value

We now consider an allocation strategy that finds the optimal trade-off between product yield and transport costs by optimizing the net value of the allocation plan. The objective function that reflects this strategy is

$$\max \{ E(Y) - E(T) \}. \tag{7}$$

The corresponding allocation plan is depicted in Figure 3.

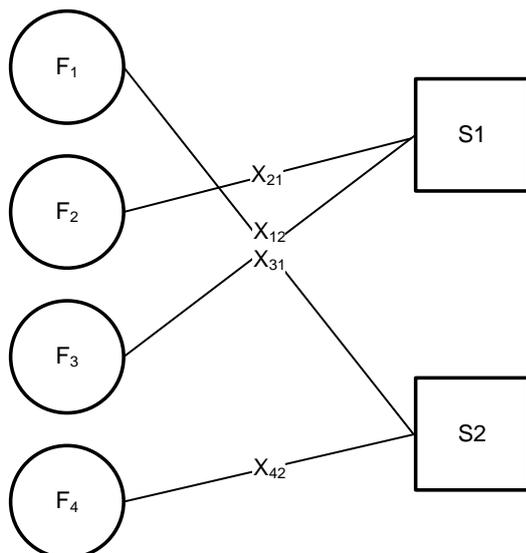


Figure 3 Example allocation based on optimized net value

In the next paragraph the performance of this allocation strategy is compared with the previously discussed allocation strategy that simply minimizes transport costs and that is currently employed by our industrial partner.

The performance of the two discussed allocation strategies with respect to transport costs, gross carcass yield and net value of the allocation plan is presented in Table 1.

<i>Allocation strategy</i>	<i>Transport costs $E(T)$</i>	<i>Gross yield $E(Y)$</i>	<i>Net value of allocation plan $E(NV)$</i>
Minimize transport costs	€ 263.-	€ 28097.-	€ 27834.-
Optimize net value	€ 348.-	€ 28577.-	€ 28228.-

Table 1 Allocation performance of running example

Table 1 reveals that the allocation strategy affects the net value of the allocation plan. This small scale example illustrates how the use of quality information in logistics decision making can improve the match between supply and demand. Consequently it can generate a higher net product yield, even though the transport costs are higher. In the following section similar methods are described to show how similar logic can be applied to larger allocation problems.

3. Solution method

In the following sections, we will employ our mathematical model to evaluate the impact of different decision criteria in livestock allocation planning of multiple meat processing locations. Mathematical programming models can be used to find optimal solutions of complex problems. These models are flexible in setup, and technical details and operational constraints can be included easily. We use a Mixed Integer Linear Programming (MILP) model to evaluate the impact of different decision criteria in livestock planning of meat processors with multiple locations. The reason is that MILP formulation is easy and intuitive. Furthermore, a variety of MILP solvers is available, and for the problems of the size we consider (allocation of up to 100 livestock batches) MILP works well and gives optimal allocation plans.

More specifically, we directly transformed the formulas given in the problem description into a MILP model using the standard solver (mmsprs) of Fico Xpress. The two supply strategies in this model are represented by different objective functions, based on formula 6 and 7. The transport costs, the gross product yield and the net value of the allocation plans were calculated using formula 3, 4, and 5 respectively.

4. Experimental section

In this section we will compute an allocation plan for a realistic input data set. A total of 49 farmers ($I = 49$) supply livestock batches to 6 different processing locations ($J = 6$), comprising of a total of 7148 animals. We will use farmer-specific quality estimates for three carcass classes ($K = 3$). The first two classes on average account for 49% of all processed animals. All the other animals are grouped into the third quality class, and we assume that all the animals in this class have the same product yield at different processing locations.

Real-life transport distances in km from farms to the processing locations are available. In order to compute transport costs in € per animal, the transport distances were multiplied with a transport price of € 0.0074 per km per animal (based on short-range transports, Baltussen et al., 2010).

For each farmer, a dataset with quality data of five historical deliveries was available. This dataset contains information on quality features like weight, lean meat ratio, and fat layer thickness of animals in these deliveries, and was used to group all animals into three carcass quality classes. The classified data of these five historic deliveries was used to develop five different scenarios ($L = 5$) for what ratio a farmer might deliver in a respective quality classes in a future delivery (q_{ikl}). For simplicity, equal probabilities for each of the five different scenarios (m_{il}) are considered (20 %), however a more thorough statistical analysis may be applied in order to refine scenario probabilities.

We assume that all 6 processing locations have a processing capacity of 1250 animals per period: $\{c_1, = 1250, c_2, = 1250, c_3, = 1250, c_4, = 1250, c_5, = 1250, c_6, = 1250\}$. This gives a total capacity of 7500 animals, which leaves a capacity surplus of 4.7 % compare to the number of animals to be processed (7148).

We assume the following prices for processing locations and carcass classes: $\{p_{11} = € 82, p_{12} = € 62, p_{13} = € 75, p_{21} = € 85, p_{22} = € 58, p_{23} = € 75, p_{31} = € 97, p_{32} = € 63, p_{33} = € 75, p_{41} = € 67, p_{42} = € 55, p_{43} = € 75, p_{51} = € 75, p_{52} = € 65, p_{53} = € 75, p_{61} = € 78, p_{62} = € 60, p_{63} = € 75\}$.

4.1. Results

The developed MILP model was used to obtain optimal allocation plans for the two different supply strategies: minimized transport costs and optimized net allocation value. Results show that 30 out of 49 farmers are allocated to different processing locations based on the two supply strategies that were considered. The performance of both allocation plans with regard to transport costs, gross yield, and net value are summarized in Table 1.

<i>Supply strategy</i>	<i>Transport costs</i> $E(T)$	<i>Gross yield</i> $E(Y)$	<i>Net value of allocation plan</i>
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			$E(NV)$
Minimized transport costs	€ 6055	€ 516499	€ 510444
Maximized net profit	€ 8824	€ 526720	€ 517896

Table 1 Performance of different supply strategies

The results in Table 1 show that the yield improvement brought by effectively using quality information in this allocation plan exceeds the rise in transport costs, resulting in a 1.5% net value increase in the allocation plan. Since the profit margins are typically low in the meat processing industry, a 1.5 % increase of the net value of an allocation plan would yield a significant competitive advantage. A geographical overview of the different allocation plans is given in Figure 4 (the underlying map is not displayed for confidentiality reasons).

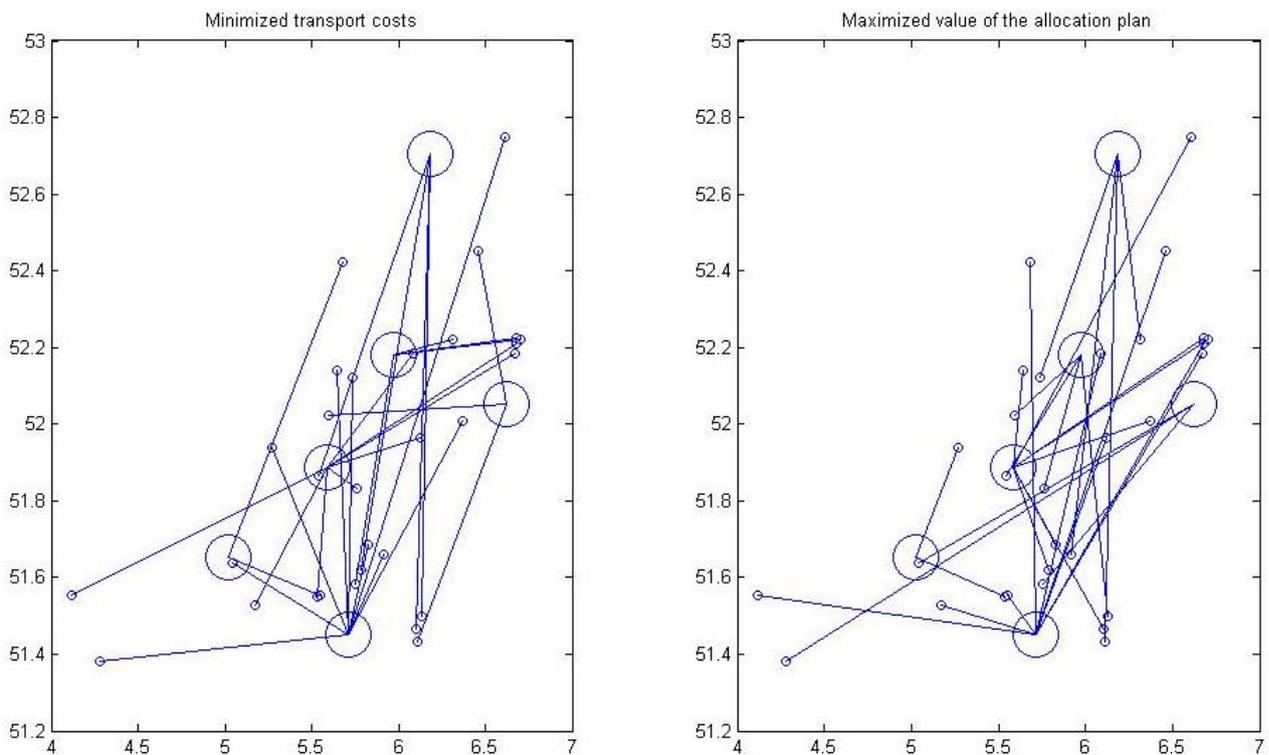


Figure 4 Geographical overview of different allocation plans

Figure 4 shows the geographical locations of the processing locations, the farms, and the links between them for both supply strategies. Note that our model uses real transport distances rather than geographical distances (represented by the straight lines in the picture).

4.2. Sensitivity analysis

The results given in the previous section give insight into the applicability of quality information in the supply planning of meat processors. These results, however, do not show whether the applied technique is robust for changes in input data. In this section, we will therefore look at the sensitivity of the proposed allocation strategies to changes in the most important parameters, namely location-specific product yield for carcass classes (p_{jk}) and transport costs (d_{ij}). The model can also analyze the effects of other changes (e.g. the effect of changing location specific processing capacities (c_j).

We will assess the impact of the following input changes: the existing transport costs (d_{ij}) are multiplied by factors $\{0.10, 0.30, 0.50, 0.75, 1.00, 1.25, 1.50, 1.75, 2.00, 2.50, 3.00\}$; new location-specific carcass class product yields (P_{jk}) are obtained by multiplying the location-specific deviation from the average value by the factors $\{0.10, 0.30, 0.50, 0.75, 1.00, 1.25, 1.50, 1.75, 2.00, 2.50, 3.00\}$. For instance, the average product yield of a class 2 carcass over all 6 processing locations is € 60.50, and P_{12} is € 62. With a multiplication factor of 2, this product yield of a carcass class two would become $60.50 + 2 * (62 - 60.50) = € 63.50$.

The outputs of the optimization model of both allocation strategies are compared in Figure 5 for varying transport costs (left graphs) and location specific product yield (right graphs). The impact of these changes is assessed on (i) the relative improvement in net value (Formula 5) (upper graphs) and (ii) the ratio of livestock batches that is allocated to the same processing locations by both allocation strategies (lower graphs). This figure does not give information on cross-sensitivity of transport costs (d_{ij}) and price variations (p_{jk}), but this might be interesting to analyze in future work.

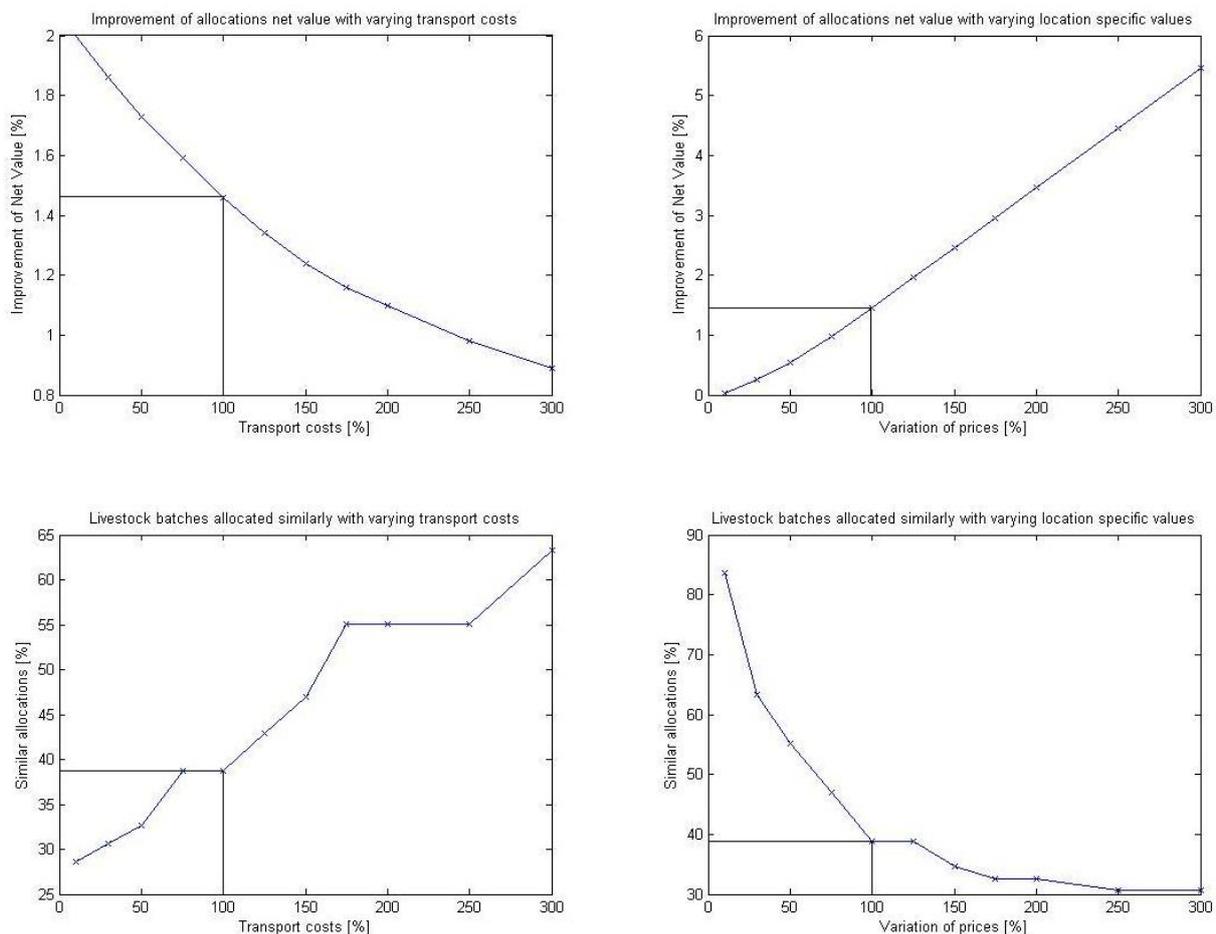


Figure 5 Impact of changes in price variance and transport costs

From Figure 5, we conclude that the net value improvement of quality information use in supply planning is reduced by increasing transport costs or by decreasing price variations. This is intuitive, since higher transport costs will make it less attractive to re-allocate animals to the non-nearest slaughterhouse, whereas lower variation in location specific price also reduce the willingness to accept higher transport costs. Therefore, either increasing transport costs or decreasing price variations will make it less attractive to re-allocate livestock batches

when quality information is considered. Lower transport costs or higher location specific variation will have the opposite effect. Figure 5 also reveals that the supply planning is more sensitive to changes in price variations than it is to changes in transport costs. However, despite large increases (up to 300 %) in transport costs or large reductions (up to 90 %) in price variations, using quality information in supply planning is still commercially viable.

5. Discussion and future works

The proposed method to deal with inherent quality differences of livestock provided by farmers has the potential to increase net product yield and boost profits of meat processing companies. Therefore this case study demonstrates the applicability of the QCL framework suggested by van der Vorst et al. (2009). Several issues regarding this case-study could, however, be addressed in future research.

This research is based on a MILP model. For the number of instances and constraints considered in this case, this model gave optimal solutions within a short time span. For larger or more complex instances, the use of MILP models might be inefficient or infeasible. In that case, heuristic methods might be developed in order to find 'near-optimal' allocation plans.

Another direction for improvement concerns the method adopted for quality estimation. Further research could aim at developing and assessing alternative quality estimation methods in order to improve the accuracy of quality estimates. These methods may include larger datasets or methods to take into account seasonal trends.

Our objective in this research was to employ estimates on supplied product quality in order to maximize the expected net profit of an allocation plan. The reliability of a given supply plan, however, was not addressed in our model. Including the reliability of quality estimates in the allocation planning, for instance by including constraints on worst-case scenarios, could be an interesting and relevant direction to consider in future work.

Future work might finally include the use of more operational constraints, like transport costs related to livestock group sizes, restricted access to processing locations for livestock groups or combined livestock transports.

This research focused on the use of quality information at the supply planning of meat processors. Furthermore, an interesting direction to pursue could be to look how quality control at other places in the supply chain could be applied to improve overall supply chain performance.

6. Conclusion

In this study we proposed an approach that uses quality estimates for allocating farmer livestock batches to meat processing locations. We showed that our approach can potentially improve financial performance of meat processing companies when compared to the current practice of simply minimizing total transport costs. To show this, we developed a strategy that optimizes the benefits of using quality estimates (by achieving a higher yield for certain quality classes) while incorporating extra transport costs incurred for not transporting the animals to the nearest processor.

The quality-based allocation was compared to the current allocation strategy using a MILP model. This model was tested on both a small motivating example and a realistic size problem. In the realistic size problem 49 livestock groups were allocated to 6 processing locations. The impact of the different optimal allocation plans was assessed with respect to transport costs, total carcass yield and the net value of the allocation plan (carcass yield – transport costs).

We observed an improvement of 1.5 % for the net value of the optimal allocation plan obtained by considering quality estimates. This yields, given the low margins in the meat processing industry, a significant improvement of the companies profitability. Furthermore, we analyzed the sensitivity of the model to changes in transport costs and variations in carcass class prices at different locations. This analysis revealed that changes in transport costs and variations of location-specific price levels affect the improvement in net yield as a result of using quality information. However, even for changes up to 300 % for these inputs, the use of quality estimates for allocation planning remains considerably advantageous.

These results indicate that using quality estimates in supply planning of meat processors is promising and that applying such methods in supply planning of meat processors is likely to strongly impact the overall livestock yield at multi-location meat processing companies. Furthermore, we conclude that MILP models provide a suitable and easy-to-use method for finding optimal solutions for allocation problems of realistic size and complexity.

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