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# Application of stochastic programming to reduce uncertainty in quality-based supply planning of slaughterhouses

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**Abstract** To match products of different quality with end market preferences under supply uncertainty, it is crucial to integrate product quality information in logistics decision making. We present a case of this integration in a meat processing company that faces uncertainty in delivered livestock quality. We develop a stochastic programming model that exploits historical product quality delivery data to produce slaughterhouse allocation plans with reduced levels of uncertainty in received livestock quality. The allocation plans generated by this model fulfill demand for multiple quality features at separate slaughterhouses under prescribed service levels while minimizing transportation costs. We test the model on real world problem instances generated from a data set provided by an industrial partner. Results show that historical farmer delivery data can be used to reduce uncertainty in quality of animals to be delivered to slaughterhouses.

**Keywords** supply chain · uncertainty · food supply chain networks · stochastic programming · allocation planning · quality controlled logistics

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## 1 Introduction

According to recent studies [8, 1], several retail and market segments show growing interest in high-quality, healthy and convenience food. As a result, demand for product quality features has become more segmented and product variety has increased significantly. Segmentation in consumer demand for food can be related to all kinds of quality attributes such as taste or color, ease of use, and production process characteristics (e.g. hygiene standards adopted or sustainability issues) [4]. By differentiating production strategies and processes to exploit this segmented demand, food processors may create extra value [8]. To realize this, demand preferences of market segments must be translated into clear product and process specifications for different supply chain actors [14, 9]. Furthermore, supply chain actors need efficient planning systems to match product quality with variable, market specific demand [10].

Recent developments in ICT and sensing technology have improved the means to gather, communicate and process information on product quality [12]. This allows food processors to gather and process more product quality information and, in turn, increases opportunities to direct products to market segments that value their specific product characteristics most [19]. However, to capture these opportunities, companies need novel logistics concepts and planning systems that exploit product quality information effectively.

Use of product quality information appears to be important in the meat processing chain due to the large variety in product quality, market segments, and processing options. Differences in farmer production and breeding systems result in variation in quality features such as carcass weight, fat layer thickness, and lean meat percentage [14], whereas market segments vary with respect to preferred quality features [8] (e.g. Japan prefers fat meat, Greece prefers light and lean carcasses). These preferences result in differences in economic value of a carcass in different markets. Since slaughterhouses differ in processing equipment and handling procedures, they also differ in end products they can produce and customer markets they can deliver to. This variation in end products and markets may limit the match between available and demanded product quality features at slaughterhouses, resulting in reduced product yield and poor customer satisfaction.

A process analysis of a large European pork processor revealed that in current operations no information on animal quality features is gathered until animals are slaughtered at the slaughterhouse. The current slaughterhouse supply strategy consists of transporting animals to the nearest slaughterhouse (given capacity constraints) to minimize transportation costs. By doing so, the inherent variation in quality between animals of different farmers, caused by differences in farmer production systems, is not exploited to match demand for product quality features of individual slaughterhouses. Furthermore the company faces large uncertainty in product quality received at their individual slaughterhouses. We argue that, to improve carcass yield and customer satisfaction, one should consider product quality information while allocating livestock to slaughterhouses. Of course, a quality-based allocation strategy implies that livestock batches might be transported over longer distances. This, in turn, could affect transportation costs. The marginal benefit of transporting animals over longer distances to target specific markets should therefore outpace the increase in transportation cost. As the reader may imagine, an advanced planning system is essential to capture these complex trade-offs.

In this paper opportunities associated with use of product quality information in supply planning of a meat processor are assessed. Based on data supplied by an industrial partner, we investigate how product quality information can be used to improve the match between supply and demand for product quality features at slaughterhouses.

The remainder of this paper is organized as follows: In Section 2 we discuss the embedding of the research question in literature and the research approach followed in this paper. Section 3 gives a detailed description of the characteristics of the livestock allocation problem. Section 4 presents the formulation of the stochastic programming problem. Section 5 describes the numerical experiments with the model. Section 6 gives a brief conclusion on the research questions and directions for possible further research.

## 2 Literature on the research question and approach

This section presents a review of relevant literature, both on use of product quality of information in food supply chains and on supply chain models dealing with uncertainty. An extensive literature review by Akkerman et al. [1] on quantitative operations management approaches and challenges in food distribution concludes that effective use of product quality information in decision making was seen in some recent work, but that it remains a challenging research area. Several examples have been found in literature that incorporate use of product quality information. Van der Vorst et al. [19] introduce a framework called "*Quality Controlled Logistics*" that specifically addresses use of product quality information in logistics decision making to improve the match between demanded and supplied quality features. Dabbene et al. [7] used quality decay models in discrete event simulation to minimize logistics costs while maintaining pre-specified quality levels. Rong et al. [15] developed a Mixed-Integer Linear Programming (MILP) model to integrate food quality in production and distribution planning using temperature at different supply chain stages as decision variables in a logistical network. Van der Vorst et al. [20] developed a discrete event simulation software package that incorporates continuous quality decay effects into a simulation toolbox called Aladin™. Most literature contributions in this field, however, fail to incorporate the stochastic nature of variation in product quality [1]. To address presence of uncertainty in food supply chains, Akkerman et al. [1] suggest use of hybrid models that combine both mathematical programming with simulation techniques. An interesting contribution based on hybrid modelling was presented by Dabbene et al. in [6] and [7]. An extensive literature review on quantitative supply chain models dealing with uncertainty presented by Peidro et al. [13] classified literature contributions in this field based on three characteristics. These are (i) source of uncertainty (demand, process or supply uncertainty), (ii) problem type (operational, tactical, strategic), and (iii) modelling system (analytical, artificial intelligence, simulation, and hybrid models). The livestock allocation problem presented in this paper deals with supply uncertainty at a tactical/operational level. The review above revealed that very limited research is done on tactical and operational models that incorporate supply uncertainty. Furthermore, the few existing works focus on uncertainty in supplier *capacity*. To the best of our knowledge, no work in supply chain planning has so far investigated uncertainty in supplied product *quality*.

The focus of this paper is on the uncertainty in the quality of the supply of farmers to slaughterhouses. The question is how we can use historical information on the number of animals delivered by a farmer and on the quality features (i.e. fat layer thickness, weight, etc) of each of the delivered animals to support decisions on the allocation decisions of deliveries to slaughterhouses. Several contributions can be found in literature that are based upon hybrid sample-based modelling systems. These contributions do, however, deal with uncertainty with respect to supplied or demanded quantity. To the best of our knowledge, this work is the first in which a sample-based solution method is employed to tackle uncertainty in supplied product quality at a tactical/operational level.

## 3 Problem description

We consider the case of a large European meat processor that owns multiple slaughterhouses. Each day this company buys livestock batches from a large, fixed group of farmers. This livestock is then transported by the company to one of its slaughterhouses. A variety of carcass quality features (e.g. fat layer thickness, weight, etc.) are measured after slaughtering. Carcasses are then sorted into separate quality classes based on these quality features. These quality classes are used as a basis for farmer payments, and to match carcasses with orders to be produced. The company currently allocates animals from farms to slaughterhouses based on minimizing total livestock transportation costs, i.e. allocate from farm to the nearest slaughterhouse given capacity constraints. The motivation of our research is that the decision maker would like to determine to which slaughterhouse individual livestock batches should be allocated to reduce the level of uncertainty in quality at the slaughterhouses.

We begin by describing the supply network. The network comprises of farms that deliver batches of livestock and slaughterhouses that consider a number of carcass quality classes. The number of animals a farmer delivers is known in advance since farmers have to indicate the number of animals they will supply several days before the actual delivery. The processing company has the freedom to process these animals at one of its slaughterhouses, and normal practice is to transport all animals from one farm to a single slaughterhouse, since mixing animals from different farms on a truck is forbidden by current health and safety regulations. Each slaughterhouse has a processing capacity in number of animals it can process each day, and a demand for animals of a specific carcass quality class. This demand is assumed to be known in advance, due to existing contracts and commitments with downstream meat processors and retailers in the chain. The animal transportation costs only depend on the distance. Costs for loading and unloading of livestock, veterinary inspection, etc. are assumed to be similar for all farmers and slaughterhouses, and therefore left out of consideration.

Every animal delivered to the slaughterhouse belongs to a single quality class. For a given delivery, the fraction of animals a farmer delivers in a quality class is unknown beforehand. Collecting quality information on all relevant animal quality features at farm level before animals are transported is not a realistic option with current technologies. This is due to high investment and operational costs of measuring livestock quality features at farm level. We investigate the use of historical farmer quality data in the planning of the livestock allocation to reduce uncertainty in quality. Finding an allocation plan, based on stochastic quality, that fulfils demand with sufficiently high probability while minimizing transportation costs is a problem of optimization under uncertainty. Several approaches exist for modelling and solving problems of optimization under uncertainty [17], of which stochastic programming is a widely adopted method [3]. A recent literature review, however, revealed that this technique has only seen limited application in sourcing decisions [5].

## 4 Stochastic programming model

We now introduce a stochastic programming model (SP) for the livestock allocation problem discussed in Section 3 and a procedure to produce allocation plans with reduced levels of uncertainty and cost. For a background on concepts underlying this SP model the reader is referred to Ben-Tal et al. [2] and Birge and Louveaux [3]. The indices, data, and variables used in this SP model can be found in Table 1

**Table 1** Model indices, data and variables used in this paper

| | |
|---|---|
| *Indices* | |
| $i$ | farm index, $i = 1, \dots, I$ |
| $j$ | slaughterhouse index, $j = 1, \dots, J$ |
| $k$ | quality class index, $k = 1, \dots, K$ |
| $l$ | historical delivery, $l = 1, \dots, L$ |
| $m$ | iteration counter used in Algorithm 1 |
| $n$ | scenario number, $n = 1, \dots, N$ |
| *Input data* | |
| $a_i$ | animals delivered by farmer $i$ in number of animals. |
| $d_{ij}$ | transportation costs from farm $i$ to slaughterhouse $j$ in € per animal |
| $c_j$ | processing capacity of slaughterhouse $j$ in number of animals |
| $\zeta_{ik}$ | uncertain fraction of animals from farmer $i$ in quality class $k$, $\sum_k \zeta_{ik} = 1$. |
| $h_{jk}$ | demand for carcass quality class $k$ at slaughterhouse $j$ in number of animals |
| $\alpha$ | minimum required service level for fulfilling demand $h_{jk}$, $\alpha \in [0, 1]$ |
| $\mathbb{Q}_i$ | set of observed deliveries for farmer $i$ |
| $\mathbf{z}_{il}$ | fraction vector of delivered quality by farmer $i$ in historical delivery $l$ |
| $\xi_{ikn}$ | quality delivered by farmer $i$ in quality $k$ under scenario $n$ |
| $\Xi_n$ | matrix of quality deliveries under scenario $n$ |
| $\mathbb{S}$ | finite subset of possible outcomes of random variable on deliveries all farmers |
| $\mu_{ik}$ | average fraction of quality delivered in quality class $k$ by farmer $i$ |
| $cv_{ik}$ | coefficient of variation in quality delivered in quality class $k$ by farmer $i$ |
| *Decision variables* | |
| $X_{ij}$ | allocation of animals from farm $i$ to slaughterhouse $j$, $X_{ij} \in \{0, 1\}$ |
| $Y_{jkn}$ | demand fulfilment at slaughterhouse $j$ for quality class $k$ under scenario $n$, $Y_{jkn} \in \{0, 1\}$ |
| *Derived decision variables* | |
| $TC$ | transportation cost in € |
| $sl$ | service level, $sl \in [0, 1]$ |

The objective function is the total transportation cost $TC$ associated with a given allocation plan:

$$TC = \sum_{i=1}^{I} \sum_{j=1}^{J} X_{ij} a_i d_{ij} \tag{1}$$

An allocation plan should fulfil the following constraints

$$\sum_{i=1}^{I} X_{ij} a_i \leq c_j \qquad j = 1, \ldots, J, \tag{2}$$

$$\sum_{j=1}^{J} X_{ij} = 1 \qquad i = 1, \ldots, I, \tag{3}$$

$$\Pr\left\{ \sum_{i=1}^{I} X_{ij} \zeta_{ik} a_i \geq h_{jk} \right\} \geq \alpha \qquad j = 1, \ldots, J, k = 1, \ldots, K, \tag{4}$$

The objective function $TC$ in (1) is to be minimized. Equation (2) ensures that slaughterhouse capacity is not exceeded. Equation (3) takes care of the allocation of each animal-batch to a slaughterhouse. The chance constraint in Equation (4) guarantees that demand for quality ($h_{jk}$) is met at required service level $\alpha$. This requirement can be dependent on the slaughterhouse and quality class, but for our case it is sufficient to assume one uniform requirement $\alpha$. The probability at the left hand side depends on the stochastic variate that is used to model the uncertain parameter $\zeta_{ik}$.

The main question in this research is how the allocation plan can be improved with the available information from the past. This information consists of quality data available from $L$ historical deliveries (with $l = 1, \ldots L$), for each of the $I$ farmers (with $i = 1, \ldots, I$), captured in measured fraction vectors $\mathbf{z}_{il}$. For the model of stochastic fraction vector $\zeta_{ik}$ we take the support as the set of observed vectors $\mathbb{Q}_i = \{\mathbf{z}_{il}, l = 1, \ldots, L\}$ for each farmer $i = 1, \ldots, I$ where each element in $\mathbb{Q}_i$ has the same probability of $1/L$ on occurrence. Assuming independence between the farmers defines an outcome space $\mathbb{Q}_1 \times \mathbb{Q}_2 \times \ldots \times \mathbb{Q}_I$ with $N = L^I$ possible outcomes, each with a probability $1/N = (1/L)^I$.

The chance constraint (4) can then be expressed exactly by what is called in literature on stochastic programming (e.g. [3], [11]) scenario-based modeling. Let a binary variable $Y_{jkn}$ express that demand $h_{jk}$ is fulfilled ($Y_{jkn} = 1$) when outcome $n = 1, \ldots, N$ takes place. Let $\Xi_{kn} = (\xi_{1kn}, \xi_{2kn}, \ldots \xi_{Ikn})$ be a matrix of outcome $n$ where column $\xi_{ikn}$ corresponds to fraction vector $\mathbf{z}_{il}$ of outcome $n$ in $\mathbb{Q}_1 \times \mathbb{Q}_2 \times \ldots \times \mathbb{Q}_I$. Then chance constraint (4) is equivalent to

$$\sum_{i=1}^{I} X_{ij} \xi_{ikn} a_i \geq Y_{jkn} h_{jk} \qquad j = 1, \ldots, J, k = 1, \ldots, K, n = 1, \ldots, N, \tag{5}$$

$$\sum_{n=1}^{N} Y_{jkn} \geq \alpha N \qquad j = 1, \ldots, J, k = 1, \ldots, K, \tag{6}$$

As the number $N$ of possible outcomes is, even for relatively small number of farmers $I$ and historical observations $L$, very large, this MILP model only has a theoretical meaning. However, we are interested in obtaining allocation plans with minimized transportation costs that satisfy chance-constraints according to their threshold $\alpha$. In scenario-based modeling, it is usual to consider a finite subset $\mathbb{S}$ with a limited number (e.g. $N = 160$) of samples $\Xi_n$ of the possible outcomes of the possible outcomes $\xi_{ikn}$ of random variable $(\zeta_{1k}, \zeta_{2k}, \ldots, \zeta_{Ik})$. The observed service level $sl$, defined as

$$sl = \min_{j,k} \frac{1}{N} \sum_{n} Y_{jkn}, \tag{7}$$

is only an estimation of the service level of allocation plan $X$, but fulfils the chance constraint $sl \geq \alpha$.

After optimization of the MILP model with the limited number of $N$ samples in the optimization set $\mathbb{S}$, one can evaluate the actual service level belonging to the resulting allocation plan. We use $\hat{}$ to denote variables used for evaluation purposes. We evaluate the actual service level of an allocation plan by estimating $\hat{sl}$ using a large evaluation set $\hat{\mathbb{S}}$ of $\hat{N}$ samples, e.g. $\hat{N} = 5000$. To ensure comparable model solutions, the same optimisation sample set $\mathbb{S}$ and evaluation sample set $\hat{\mathbb{S}}$ are used throughout different variants and scenario comparisons.

To gain insight in the trade-off between uncertainty reduction, expressed as service level $\hat{sl}$, and transportation cost $TC$ we present Algorithm 1. In this algorithm we vary $\alpha_m$ in a systematic way for each iteration $m$, generating allocation plans $X_m$ and measuring the corresponding transportation cost $TC_m$ and observed service level $\hat{sl}_m$. The reached service level $sl_m$ for the optimization sample set $\mathbb{S}$ is used to set a new value for parameter $\alpha_{m+1}$. It is increased by one sample such that the old plan becomes infeasible and the uncertainty in the new plan is reduced accordingly. Notice that $sl_m \geq \alpha_m$ and many times due to the discrete values of the plan and samples it is larger, i.e. $sl_m > \alpha_m$. The algorithm generates an approximation of the Pareto front that minimizes transportation cost $TC$ and maximizes the observed service level $\hat{sl}$. After filtering out the dominated $TC_m, \hat{sl}_m$ combinations the remaining allocation plans are proposed to the decision maker. This allows the decision maker to make a conscious choice for one of the generated allocation plans $X_m$.

**Algorithm 1** $TC$-$\hat{sl}$ (in: sets $\mathbb{S}, \hat{\mathbb{S}}$, problem data, out: $TC, \hat{sl}$ front)

```
Set m = 1, α_1 = .6 and N = |S|
Solve MILP with α_1, sample set S generating plan X_1
while  X_m feasible plan and α_m < 1
    determine ŝl_m of X_m based on samples in Ŝ
    α_{m+1} = sl_m + 1/N and m = m + 1
    if α_m ≤ 1
        Solve MILP with α_m, sample set S generating plan X_m
```

## 5 Numerical experiments

### 5.1 Problem instances

We consider a base case of the livestock allocation problem that has a similar size as the problem faced by an industrial partner. The base case concerns the delivery of livestock from $I = 72$ farmers to $J = 5$ slaughterhouses on a specific day. Recall that farmers have communicated the delivery day and batch size in advance. In total the 72 farmers deliver $\sum_{i=1}^{I} a_i = 11446$ animals. Each of the slaughterhouses has a capacity of $c_1 = c_2, \ldots, = c_5 = 2400$ animals, resulting in a total overcapacity of 4.8 %. At each of the five slaughterhouses we consider the three most important quality classes ($k$ = 1,2,3). In the dataset these represent 67.6 % of all delivered animals in past deliveries.

The number of historical observations supplied by the industrial partner is $L = 45$ for each farmer. Specifically, historical quality data ($\mathbf{z}_{il}$) is derived from a dataset on quality features of 526105 animals delivered by the 72 farmers in 45 past deliveries. Livestock transportation costs $d_{ij}$ were estimated by multiplying road distances from farm $i$ to slaughterhouse $j$ with fixed livestock road transportation costs of 0.005638 € per animal per km based on estimated truck costs of 0.264 € per km for fuel, driver (0.3125 €), and truck(0.10 €), and an average load of 120 animals. The resulting costs ranges between 0.133 € and 4.33 € for transport of one animal from a farm to a slaughterhouse.

The scenario-based MILP model has been implemented in Xpress Mosel, where the number of scenarios is taken as $N = 160$ randomly drawn samples from the outcome space. The MILP model was then fed to the solver Xpress-MP version 22.01.04 run on an Intel i7 860 CPU with 2.80 GHz and 4 GB of RAM. A common time-limit of three hours was imposed on the solution time of all instances. The reached service levels $\hat{sl}$ of the found solution were measured using the same set $\hat{\mathbb{S}}$ of $\widehat{N} = 5000$ randomly drawn samples. A summary of the main parameters in the allocation problem we consider can be found in Table 2.

**Table 2** Parameter settings in base case model

| Parameter | Value | Definition |
|---|---|---|
| $I$ | 72 | Number of farmers supplying livestock |
| $J$ | 5 | Number of slaughterhouses receiving livestock |
| $K$ | 3 | Number of quality classes |
| $L$ | 45 | Number of observations for each farmer |
| $d_{ij}$ | 0.133 to 4.33 | Livestock transportation costs in € per animal |
| $N$ | 160 | Number of samples in optimization set $\mathbb{S}$ |
| $\widehat{N}$ | 5000 | Number of samples in evaluation set $\hat{\mathbb{S}}$ |
| $\alpha_1$ | 0.6 | Initial service level in Algorithm 1 |

### 5.2 Model behaviour of the base case

The current supply strategy of the industrial partner consists of shipping animals from farms to the nearest slaughterhouse (given capacity constraints) in order to minimize transportation cost $TC$. We first analyse the impact of the current supply strategy (which supplies livestock without using quality information) on the observed service level for a specific quality class. To investigate this, the allocation model is run without constraining demand for specific quality classes, i.e. $h_{jk} = 0$. The resulting minimum cost allocation plan has an objective function value of 7636.22 €. We determine, for this allocation plan, the minimum number of animals delivered to each slaughterhouse from each quality class over the 45 available deliveries. Then, we set the target demand to 120%, 140%, and 160% of this minimum value, respectively; and we assess the service level of the original allocation plan for different slaughterhouse in each quality class for the 45 historical deliveries. The resulting aggregated service level for quality class $k = 2$ at all 5 slaughterhouses is given in Figure 1.

These results suggest that, by simply minimizing transportation cost, there is large uncertainty in the number of animals that will be received in a quality class at each of the slaughterhouses. Furthermore notice that there are large differences in the observed service level between the slaughterhouses when demand increases uniformly. This is caused by the case specific locations of farms and slaughterhouses, where most spare capacity is available at slaughterhouses at less favourable locations. Similar figures can be produced for quality class 1 and 3. These findings motivate the use of the decision support SP model.

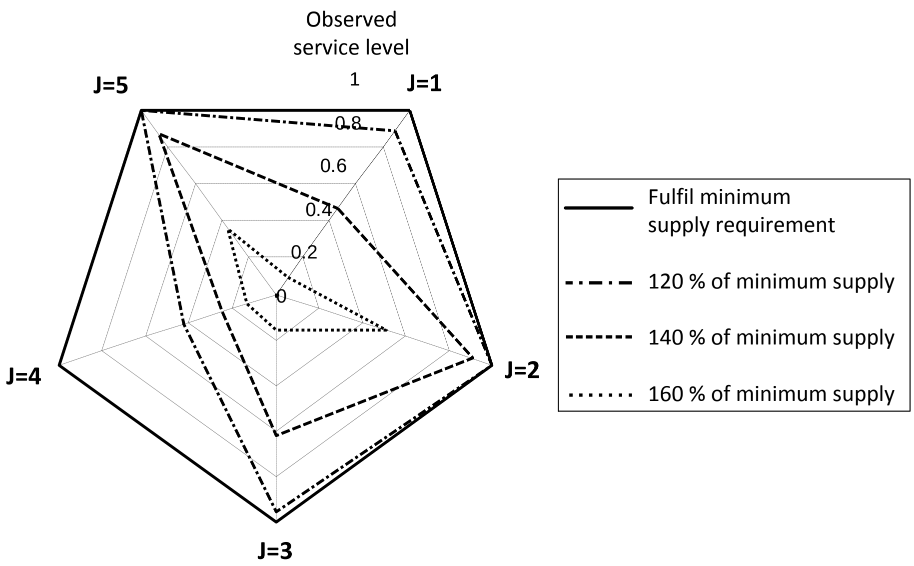


**Fig. 1** Observed service level of quality class $k = 2$ demand at slaughterhouse $j = 1$ to 5 for the minimum transportation cost plan

### 5.3 Trade-off between uncertainty reduction and transportation cost

To assess the effect of the quality based allocation model on transportation cost $TC$ we design an experiment where the demand for quality class $k$ =1 at slaughterhouse $j = 1$ is restricted while leaving demand for other quality classes and slaughterhouses unconstrained. The demand $h_{11}$ is varied between 230 and 260, whereas demand constraints for other combinations of slaughterhouses and quality classes are relaxed, i.e. $h_{jk} = 0$. Figure 2 gives insight in the trade-offs between demand variations in $h_{11}$, observed service level $\hat{sl}$ and transportation cost $TC$. This graph shows the results for varying one specific demand at one of the slaughterhouses. Varying the demand for other quality classes at other slaughterhouses provides a similar graph. Results such as the data in Figure 2 can be employed by supply planners to find allocation plans that fulfil orders for specific quality features with sufficiently high probability $\hat{sl}$ while guaranteeing low $TC$.

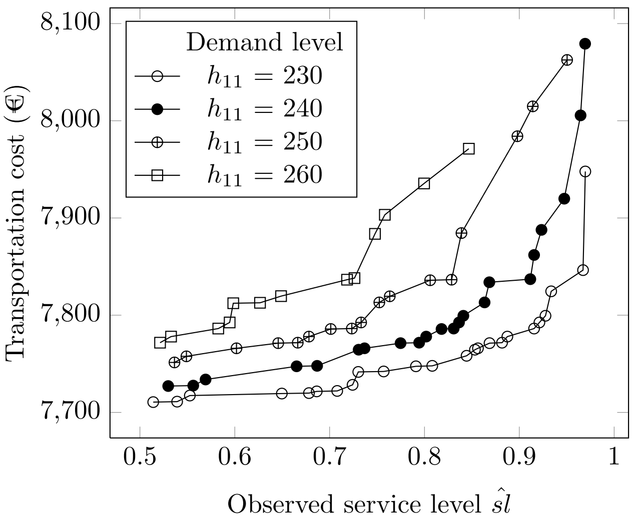


**Fig. 2** Minimum transportation cost fulfilling demand $h_{11}$ at service level $\hat{sl}$

### 5.4 Analysis on supplier variance

To study the effect of the quality variance in $\zeta$, we analyse the effect of changes in the coefficient of variation $cv$ of the quality that farmers deliver on the transportation cost $TC$ of the allocation plan. To do so, the average fraction $\mu_{ik} = E(\zeta_{ik})$ of animals each farmer $i$ delivers in a given quality class $k$ is kept constant. Notice that $\mu_{ik} = \sum_{l=1}^{L} \mathbf{z}_{ilk}/L \;\; i = 1, \ldots, I, k = 1, \ldots, K$. Now the coefficient of variation $cv_{ik} = \sigma_{ik}/\mu_{ik}$ is varied simulating lower or higher variation than in the observation set $\mathbb{Q}_i$. Figure 3 shows the resulting minimum transportation cost $TC$ when multiplying the original coefficient of variation by 0.2, 0.4, 0.6, 0.8, and 1 for each of the farmers at a constant demand ($h_{33} = 650$). Demand constraints for other combinations of slaughterhouse and quality class are relaxed, i.e. $h_{jk} = 0$. Fixing other demand $h_{jk}$ provides a similar graph.

The findings presented in Figure 3 suggest that, if a high service level is required, a more constant quality supply reduces transportation cost $TC$ needed to allocate livestock batches based on quality information. This can be explained by the reduction in supply planning uncertainty due to a more constant delivery of product quality, which reduces the need for hedging to uncertainty. Therefore if achieving a high service level is of key importance, it may be profitable to set up incentive mechanisms to motivate farmers to deliver a more constant quality. The maximum premium that can be paid to reduce the coefficient of farmer variation can be derived from model output similar to that in Figure 3.

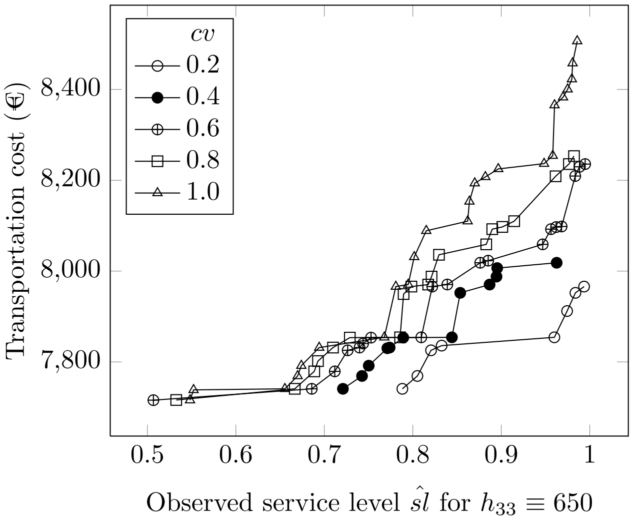


**Fig. 3** Effect of supply quality variance $cv$ on transportation cost

## 6 Conclusions and further research

For the issue of integrating quality information in logistics decision making, we study a case in meat processing industry. The question is how to generate slaughterhouse allocation plans with reduced levels of uncertainty in product quality received at individual slaughterhouses. To address this research question, a stochastic programming model has been developed that exploits historical farmer delivery data using a scenario-based approach. The computational experience demonstrates the benefits of a quality-based supply planning compared to the current practice of shipping animals to the closest slaughterhouse to minimize transportation costs.

This study shows that historical farmer delivery data can be used to reduce uncertainty in quality of animals a slaughterhouse will receive in future deliveries. The current model therefore helps to reduce uncertainty in supplied quality, and provides insight in the required transportation costs needed to fulfill demand for specific product quality classes. Future works may investigate more accurate and structured reliability measures, such as those discussed in Tarim et al. [18], in place of the chance constraints discussed in the current model. Another interesting strategy might be to penalize shortages, following Rossi et al. [16]. The model is currently positioned at an operational/tactical level. The flexible model setup, however, makes it easy to adjust the current set of constraints to make the model more suitable for operational or strategic decision making.

An interesting finding of this study was obtained from the analysis of the effects of farmer variation in product quality on transportation costs of the quality-based allocation strategy. This value gives insight in the benefits processing companies might obtain if farmers deliver a more constant product quality.

The effectiveness of the presented strategy depends on the variability in raw material quality delivered by farmers and the sensitivity of end products and processors to these quality differences. Similar strategies might be applied in other meat chains as well, given that sufficient recent farmer delivery data is available and seasonal variation in quality is limited or predictable. Furthermore, a direct trading relation between farmers and meat processors is required; buying livestock via livestock traders is not likely to yield stable and predictable livestock quality. Similar methods might be applied in sourcing decisions in other food supply chains as well, for instance by using historical data on product ripeness or microbiological quality. Future research could investigate applications such as these to counter problems caused by uncertainty in supplied product quality.

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