Automatic control of fat content in multiple batches of meat trimmings by process analytical technology

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Large shares of the pork and beef carcasses ends up as trimmings. Batches of trimmings are mainly valued by the fat content. Improved industrial control of fat content in these batches is therefore very important to secure stable quality and profitability in the industry. In this work the authors evaluated a novel strategy for automatic on-line sorting of meat trimmings into batches of predefined fat content. The optimization algorithm was based on so-called desirability functions and the input to the algorithm for each portion of trimmings is on-line measured weight and fat content. Ninety-two portions of pork trimmings (a total of 227 kg) spanning a fat range of 4.5% to 80.1% were scanned four times each with an on-line NIR system to obtain fat content estimates. All data were collected under industrial conditions in a pilot plant, and computer simulations were used to test four different sorting regimes. Results show that the sorting algorithm produces batches very close to target fat values; typical deviation is within 1%-point. The prediction error for fat at batch level was below ±1.0%-points for low fat batches and in the range 1.0–1.5%-points for high fat batches. The results demonstrate that automatic systems for on-line measurement and sorting of intact, inhomogeneous meat trimmings open up for flexible and cost-efficient production of meat batches.

Keywords

- Control of fat content
- Optimization
- Sorting
- Automatic system
- Meat trimmings

In the meat industry the economic margins are small and profitability depends on optimal utilization of the carcasses. Much of the production is controlled according to quality criteria such as muscle quality, fat, and connective tissue content. A main product from the pork and beef deboning plants is batches of meat trimmings, which are valued by fat content; the lower the fat content, the higher the purchase value. As much as 60% of the beef carcasses and about 45% of pork carcasses ends up as trimmings. Improved industrial control of fat content in these batches is very important to secure stable quality and profitability.

The traditional way of manufacturing these meat batches is that the workers in the processing line sort the trimmings manually to reach target fat per cent in the batches, typically 10, 20 or 30% fat. However, this is a difficult task and large deviations from target fat content are common. It is also a burden for the industry that new persons have to be continually recruited and trained for this task. The importance of knowing the fat content in the batches has led to the development of automatic monitoring systems. At least three different measurement principles are in use today. The systems are based on the non-invasive techniques microwaves, X-rays or near-infrared spectroscopy (NIR) (Hildrum, Wold, Segtnan, Renou and Dufour, 2006). These systems are used to check that the obtained fat content of the batches is correct. Microwave systems usually require that the meat is ground before measurement, and are therefore not suitable for intact trimmings. X-ray systems can be used on intact meat, either on already filled boxes or on streams of trimmings (SensorX by Marel Ltd, Iceland, and MeatMaster by Foss, Denmark). An advantage with X-rays is that the radiation is transmitted through large sample thicknesses and it is therefore possible to obtain quite accurate measurements of fat in very heterogeneous samples. NIR spectroscopy is also widely used for on-line determination of fat, protein and water in ground meat (Tøgersen et al., 1999), but a limitation compared to X-rays is that the NIR method has a limited penetration depth and measures mainly the upper layer (15–20 mm) when used in so-called interaction mode. If the samples are fairly homogeneous, or if the surface layer is representative for the whole sample, then the method performs well. This has been demonstrated for instance for fat determination in boxes of 20 kg of pork trimmings (O'Farrell et al, 2010). Wold et al. (2011) showed that even though the prediction error per trimming with NIR was very high (±8.7%), the prediction error for resulting batches of 10–24 kg was ±1.3% and for the larger 100 kg batches it was as low as 0.6%. Increasing accuracy with increasing batch size is achieved because random prediction errors occurring at trimming level is reduced or averaged out. The two latter studies were performed by the use of a commercial NIR imaging scanner (Tomra Sorting Solutions, Leuven, Belgium). One advantage with NIR compared to X-rays is that the systems are easier to incorporate in different production lines since radiation protection is not required and allows for more compact systems. NIR systems are also available to a lower cost and are affordable also for medium and smaller sized companies.

In the meat industry these on-line methods are used mainly to monitor the fat content in the end products. Fat content in the produced batches can be adjusted afterwards, but this is cumbersome and can also be very uneconomical, especially if the fat content has to be decreased by adding valuable lean meat. In some production plants the fat content in batches can be adjusted manually during production based on inspection of the accumulated average fat content. However, on-line methods allow the producer to move focus from feed backward control and manual adjustment to feed forward control and optimization of the process. This approach, which is often termed process analytical technology (PAT), can lead to improved and more predictable product quality, optimal use of raw materials, less waste and consequently increased profit.

Måge et al. (2013) introduced a strategy for automatic on-line sorting of meat trimmings into batches of predefined fat content. Fat content and weight were measured for every single trimming, and by an algorithm based on so-called desirability functions, it was possible to optimize the use of trimmings to reach the desired fat levels in two or more batches. In that study, NIR was used for on-line estimation of fat in the very heterogeneous trimmings. That led to large prediction errors per trimming (9.2%-points), which again resulted in systematic errors in the fat estimation of the batches. Low-fat batches were underestimated, that is, they contained more fat than estimated, while high-fat batches were overestimated. It was suggested that these systematic errors could be reduced or completely avoided if the accuracy of the fat estimation could be improved.

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The main objective of this work is to test the process analytical approach developed by MÅGE et al. (2013) on intact trimmings from pork in a setting where the accuracy of the on-line fat estimates per trimming was better. The same NIR system was used, but the trimmings were chopped into portions of smaller pieces in order to obtain more representative spectral measurements. The authors wanted to evaluate the system's ability to reach target fat levels, as well as the accuracy of fat estimation at batch level. The authors also wanted to elucidate and demonstrate the flexibility this kind of PAT can offer to meat producers. All data were collected under industrial conditions in a pilot plant, and computer simulations were used to test different sorting regimes.

Materials and methods

All the experimental work was done in a small meat cutting plant equipped with a conveyor belt for the trimmings and an on-line NIR system mounted above the belt.

Trimmings were cut from different parts of the pork carcasses, with the aim of spanning the fat content from very lean to very fat. The trimmings were cut to normal sizes and were portioned in samples of approximately 2–4 kg. Large and very heterogeneous trimmings were cut into smaller pieces of typically 10x10x5 cm by hand. Ninety-two such portions were made and scanned with the NIR system.

Each sample was scanned four times at different surfaces. That is, the sample was mixed or turned around between every measurement. The sampling then ended up with 368 NIR measurements. Each sample was weighed, summing up to a total of 226.8 kg pork meat. Each sample was then homogenized and fat content was determined in duplicate on two sub-samples using a Foss FoodScan system (Foss, Hillerød, Denmark).

The on-line NIR system was a QVision500 (Tomra Sorting Solutions, Leuven, Belgium), an industrial hyperspectral imaging scanner designed for on-line measurement of fat in meat on conveyor belts. The system was already calibrated for fat determination in pork trimmings. Each measurement took about 1 sec. Since every sample was scanned four times, four fat estimates per sample were produced. These fat estimates were used in the following sorting simulations.

Sorting simulations

The sorting task can be viewed as a multi-response optimization problem, where fat content in the different batches are the responses. Multi-response optimization problems can be solved by using desirability functions (HARRINGTON, 1965). The sorting algorithm designed to solve this particular task is described in detail in MÅGE et al., (2013). Input to the algorithm is fat content and weight of each sample in a stream. Based on the estimated current status of each batch, the algorithm will decide which batch to send the current trimming. The algorithm is rapid and can work on-line in real-time.

Before sorting starts, the main settings have to be chosen:

- Number of batches to be produced
- A target fat content for each batch
- An upper and lower fat limit for each batch. That is, strict limits close to target can be chosen, or wider limits allowing larger variation around the target.
- A steepness parameter for the desirability function. A high number (e.g. 10) favor solutions very close to the target fat content, while a small number (e.g. 0.01) give approximately equal weight to all solutions within the defined range.

In the examples below the authors have used a value of 5. It is also possible to set different steepness values for each side of the target value.

Additional restrictions can be set if needed:

- Maximum and minimum fat values per trimming going into each batch. For instance, for a lean batch, it can be decided that trimmings (portions) with fat above e.g. 40% are not allowed.
- Targets for the total amount of meat in each batch. In some cases, the sorting algorithm puts the majority of samples into the same batch. If the market demands larger volumes of other batches, it is possible to define additional restrictions to steer the production in the desired direction.
- Targets or ranges of other measured quality parameters, such as e.g. connective tissue.

Each additional restriction will naturally be on the expense of the main target, which is optimization of fat content. This means that deviation from target usually will be larger for each additional restriction.

For the simulations the authors treated the 368 NIR fat estimates of the 92 samples as 368 individual samples. This is justified by the fact that the NIR instrument measures mainly the surface, and due to mixing the surface was different for all 368 measurements. With the corresponding weights, the fat estimates made up the population of samples. The authors sorted 1000 kg of meat in each simulation, and the stream of samples was made by sampling randomly (with replacement) from the sample population. The replacement method was chosen in order to obtain independent samples. With the weights as well as the actual fat content for each trimming it was possible to calculate the current estimated and actual fat content in each batch during sorting, and thereby evaluate both the progress of each batch and the final result. By doing N= 1000 repetitions of each simulation, the authors could estimate the average performance of the method, both in terms of deviation from target and accuracy of the fat estimate. The accuracy is represented by the Root Mean Squared Error (RMSE)

$$\text{RMSE}=\sqrt{\frac{\sum_{n=1}^{N}(\text{Estimated fat in repetition } n - \text{true fat in repetition } n)^2}{N}}$$

Results and discussion

Fat content in the samples ranged from 4.5% to 80.1%, and the sample weights were in the range 1.27–3.28 kg. The accuracy of the fat estimates from the NIR system is indicated in Figure 1. All four estimates per sample are shown, and it is clear that for some of the samples the variation in fat estimate was huge. The sample with the most extreme variation had the prediction values 14.4%, 23.4%, 25.1% and 64.5%, while the actual fat content was 25.1%. This result indicates that the sample was very heterogeneous: lean on one side and fat on another.

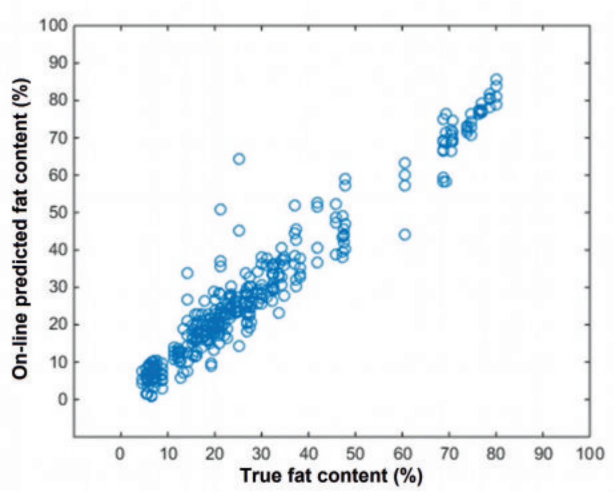

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Fig. 1: Correlation between true and on-line predicted fat content for the 92 portions of meat trimmings.

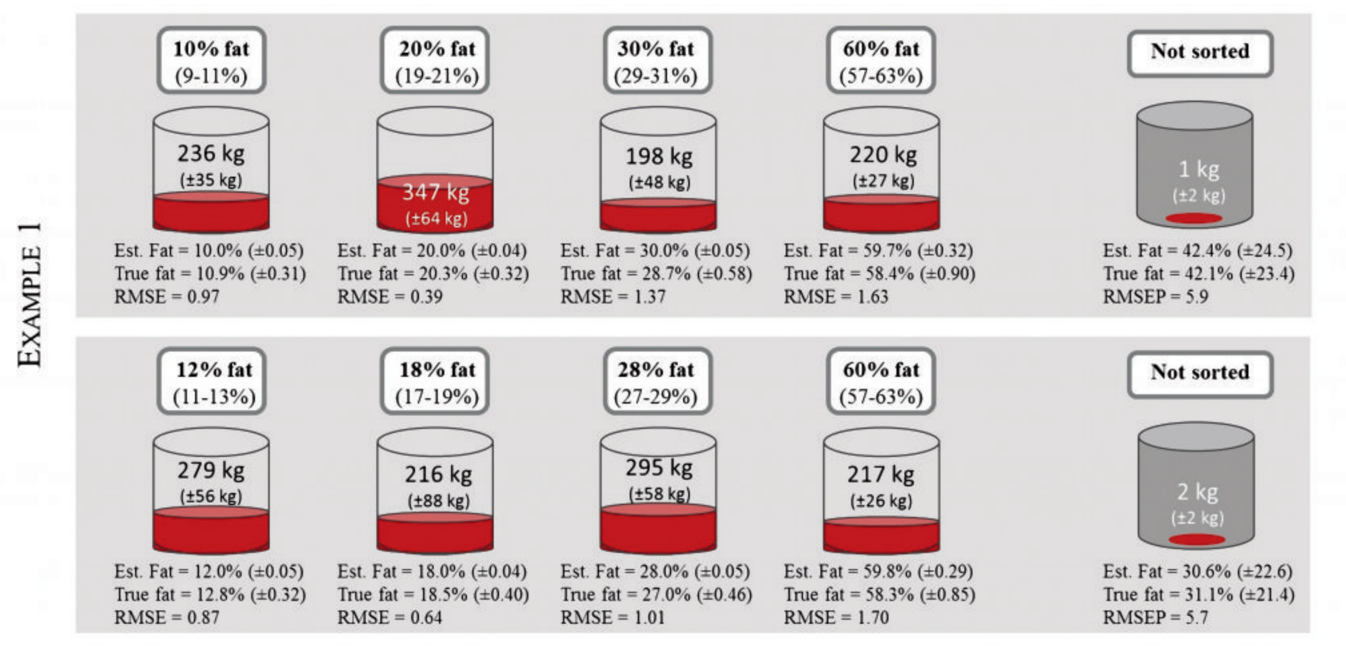

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Fig. 2a: Overview of results from Example 1

The average prediction error was 5.0%, which is quite high. This was expected since the samples were heterogeneous and the NIR system measured mainly upper layer of each sample. This prediction error per trimming/portion of trimmings was nevertheless lower than that obtained by Wold et al. (2011) and Måge et al. (2013) on intact trimmings (8.4% and 9.2%, respectively). Much lower prediction errors for fat in meat by NIR can be obtained on ground meat (0.82–1.49%, Tøgersen et al., 1999), or when averaging over for instance a 100 kg batch of trimmings (0.6%, Wold et al., 2011).

In the following results from four different simulated examples of sorting regimes are presented, to illustrate the potential benefits and a few inherent limitations. The examples are illustrated schematically in Figure 2a,b,c,d, and are designed to highlight different properties of the system:

- Example 1 illustrates the versatility with regard to changing target values.
- Example 2 shows how the system can handle differences in the raw material stream.
- Example 3 demonstrates the use of an additional constraint on the batch weight.
- Example 4 describe a possible extension of the system to also control the amount of connective tissue.

Example 1

Many meat processing plants produce batches of trimmings with fat contents around typically 10, 20, 30% as well as a high fat batch. The exact fat percent targets can vary from place to place or from day to day. One day targets could be 10, 20, 30 and 60%, the next day they could be

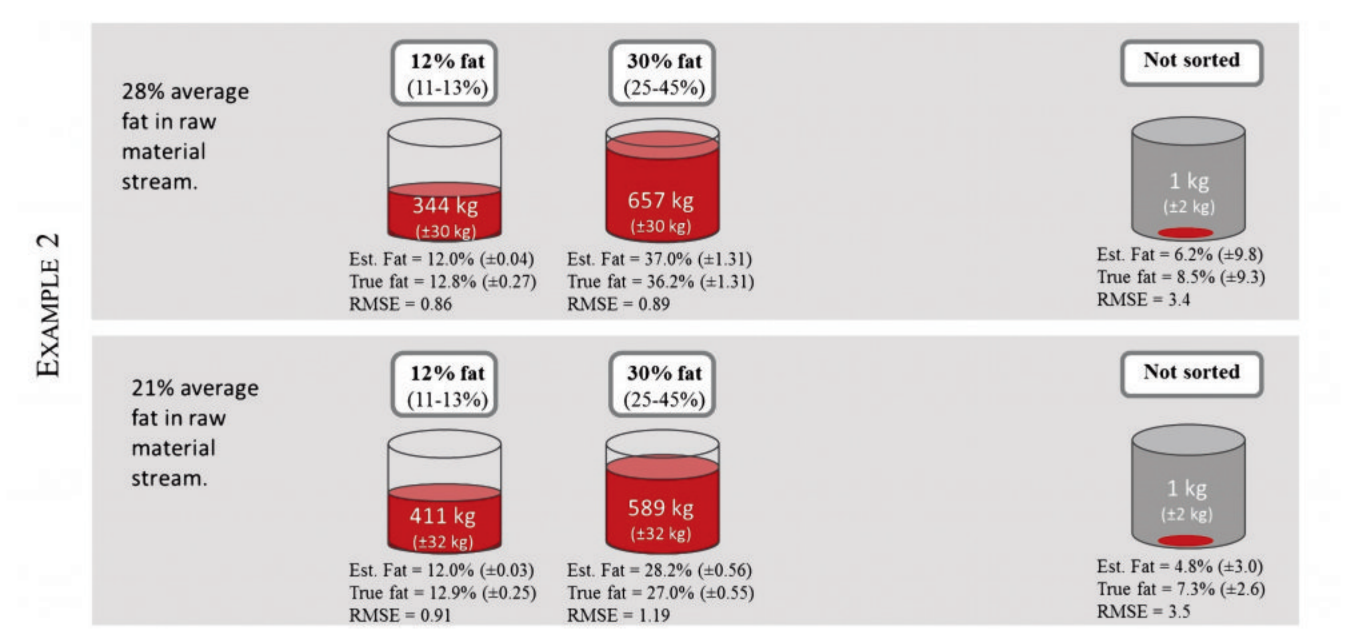

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Fig. 2b: Overview of results from Example 2

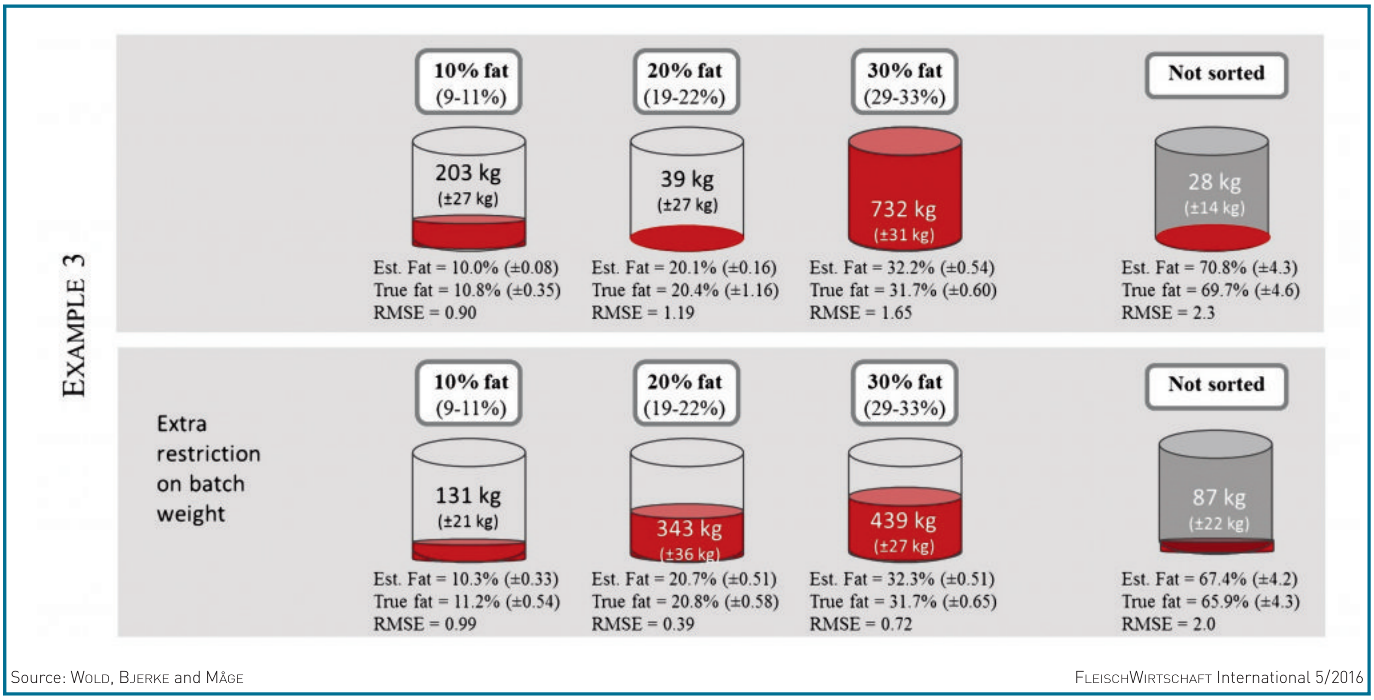

Fig. 2c: Overview of results from Example 3

for instance 12, 18, 28 and 60%, depending on customer demands. For both cases we put the following restrictions on the batches:

- A 1%-point deviation from target was accepted for the three low fat batches, while a 3% deviation was accepted for the high fat batch.
- In the two batches with lowest fat content, trimmings with fat content higher than 40% were not allowed.

The average results of 1000 repetitions of these two cases are illustrated in Figure 2a. For the low fat batches (10–20%) the actual fat content was always slightly higher than the estimated, while the high-fat (28–60%) batches were slightly over-predicted. This systematic error is due to an inherent effect also discussed by Måge et al. (2013): As long as there are prediction errors at trimming level, there will always be a systematic under-estimation of low fat batches and a corresponding over-estimation of high fat batches. This is due to the heterogeneous samples; a trimming, which is predicted to be lean, and thereby sorted into a low-fat batch, will sometimes have a much higher true fat content. However, the true value will never be much lower, and this leads to these systematic biases observed in the simulations.

In spite of this inherent systematic bias, the prediction errors and deviations from target were rather small (Fig. 2a). RMSE below 1% for the batches of lowest fat content indicates a good accuracy of the fat estimation, and represent a significant reduction compared to the error on sample level (5%). The differences between estimated value and batch target were practically zero, indicating that the sorting algorithm works very well.

As shown in Figure 2a, there was some variation in the final batch weights, but overall the size of all batches was fairly even. If a sample cannot be placed into any of the batches without breaking one or more of the restrictions, it is collected in a "not sorted" batch. In this first example, very few samples were not sorted into any of the categories (1–2 kg on average).

Figure 3 represents one randomly selected sorting process (out of the 1000 repetitions) of the first case, and shows the evolvement of fat content in each batch as a function of total weight. It can be seen that the optimization routine needs to distribute about 50 kg of meat into each batch before the estimated fat levels stabilize within the specified ranges. From then, the fat content varies slightly during the production of the batches, but the actual fat content for all batches are within the specified ranges most of the time. The same pattern was also seen for the second target value settings (not shown).

Example 2

Some processing plants typically deliver two products, one low fat product with strict limits on fat content, and one high fat batch with fewer restrictions. The fat batch can be used in for instance sausage production, in which case the fat level can vary but it is important to know the actual fat level. To illustrate this case the authors set up a sorting regime with two batches, with target values 12% and 30%. Only ±1%-point deviation from target was accepted for the low fat batch, while –5% to +15% from target was accepted for the fat batch. In addition, the 12% batch could not contain trimmings with fat con-

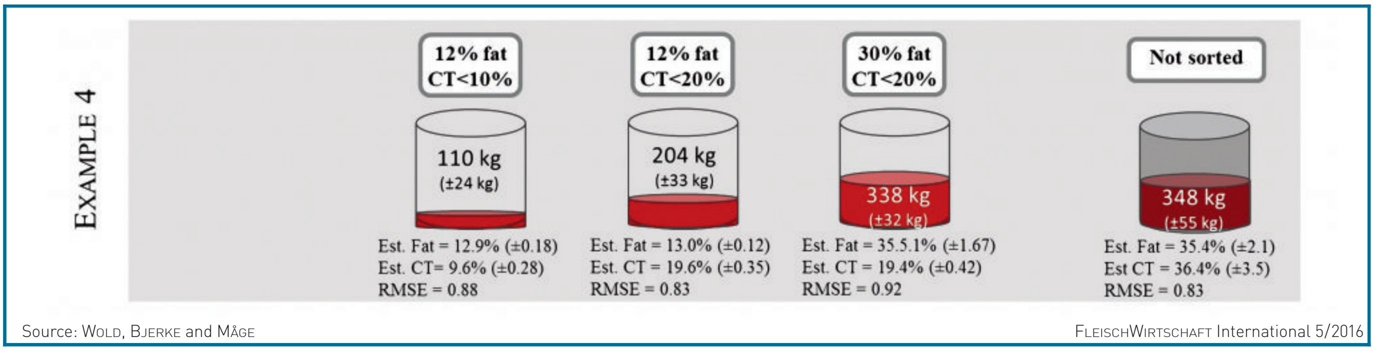

Fig. 2d: Overview of results from Example 4

tent higher than 40%, and the 30% batch could not contain samples below 15%. Two sets of simulations were run in order to investigate how different raw material streams affect the sorting:

- All the available trimmings, giving an average fat value of 28%.
- Only trimmings with fat content lower than 60%, giving an average fat value of 21%.

The average values for 1000 repetitions of each raw material stream are given in Figure 2b. In both cases the low fat batches are very close to fat target, while the two fat batches end up with quite different fat levels. The average difference between real fat level and target for the low fat batch were 0.81 and 0.86 for the two raw material sources, which means that the batch was well within the set boundaries in both cases. The average RMSE for the fat batch was 0.89 and 1.19 for the two cases. This indicates that users know quite accurately how much fat there is in the batch, although the value is far from target.

Example 3

In the next example, the authors made only three batches with target fat of 10, 20 and 30%.

For this case we put the following restrictions on the batches:

- 1, 2 and 3%-point deviation above target was accepted, respectively, for the 10, 20, and 30% batches, while 1%-point deviation was accepted below target for all batches.
- In the 10 and 20% batches trimmings with fat content higher than 40% and 50% were not allowed, respectively, and in the 30% batch, samples with fat content below 10% were not allowed.

Over a 1000 simulations of this case, an average of 28 kg of meat was not sorted (i.e. it did not fit into any of the batches), (Fig. 2c). This indicates that the meat at hand had a distribution of fat that did not fit well with the desired target values. The amount of meat in the 20%-batch was also very low in most simulations (39 kg on average), while the 10% and 30% contained on average 203 and 732 kg respectively. In order to compensate for the uneven batch sizes we put an extra element in the desirability-function, to balance the batch sizes more equally. These results are also given in Figure 2c. The batch sizes are indeed more even, at the cost of slightly higher deviations from target. The amount of meat not sorted also increased to an average of 87 kg due to the additional constraint.

Example 4

In this example, it is illustrated how to extend the system further by adding measurements of connective tissue (CT). In principle, the same NIR scanner that is used to measure fat can also estimate CT content, by identifying surface regions that are white in color and low in fat. The area of this region (calculated as percentage of total area) can act as an estimate of the amount of CT in each trimming. Just like fat, CT is heterogeneously distributed in the meat and prediction errors will be large. Equivalent to the fat estimates, the accuracy can be increased by chopping the trimmings into smaller pieces.

In order to illustrate this possibility in a sorting regime, the authors simulated CT values between 0 and 90% (of total protein) for each meat trimming. The CT values were taken from a distribution that was skewed towards smaller values (an exponential distribution with λ= 3), and linearly rescaled to values between 0 and 90. The mean CT value was 25%. We used the same target batches as in Example 2 (12 and 30% fat), but the 12%-batch was split in two: low and average CT with upper limits 10 and 20% respectively. The upper CT limit is set to 20% for the high-fat batch as well. Results of 1000 simulated sortings are visualized in Figure 2d. Only the estimated fat values are reported, as the deviations from true fat are equivalent to those in previous examples. Figure 2d shows that the fat and CT levels are within the target limits for all batches, but the estimated fat content is very close to the upper limit of 13% for the low-fat batches. The amount of meat that was not sorted has also increased, mainly due to high CT levels. Figure 4 shows the progress of one of the 1000 repetitions, and it can be seen that both the fat and CT values stabilize at around 30–50kg batch weight, which is equivalent to the results from Example 1.

Practical importance

This paper shows how automatic systems for online sorting of intact, inhomogeneous meat trimmings open up for flexible and cost-efficient production of meat batches. Implementation of these sorting algorithms would be a good step forward for the meat industry in terms of process control with regard to profit, meat quality and logistics. In addition to the obvious reduced cost in terms of labor and time, the meat industry can benefit from such systems by being able to:

- **Deliver according to specifications**

The two cases in example 1 illustrate some of the flexibility of the system; it is simple to switch between any fat targets. No system training is required, and certainly no training of manual labor. The other examples also illustrate that it is possible to set up any number of target batches, as long as the targets fit the raw material at hand. Example 4 describes how the system can be extended to also include other critical quality attributes that can be measured on-line.

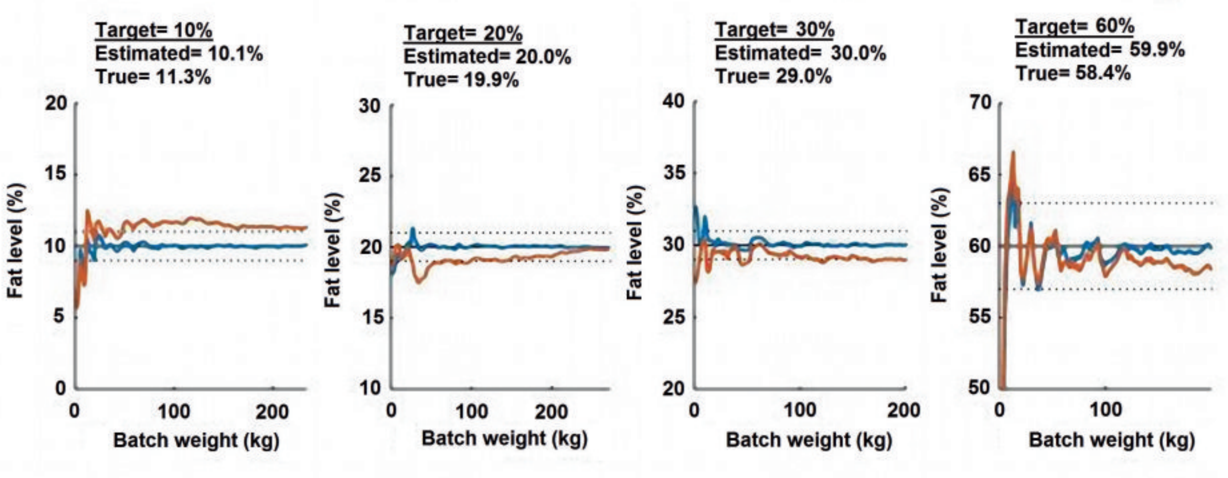

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Fig. 3: Evolving fat content as function of batch weight for one sorting process from Example 1. The blue and red line represent estimated and true fat content respectively, while the dotted lines show the upper and lower limits set in the sorting algorithm.

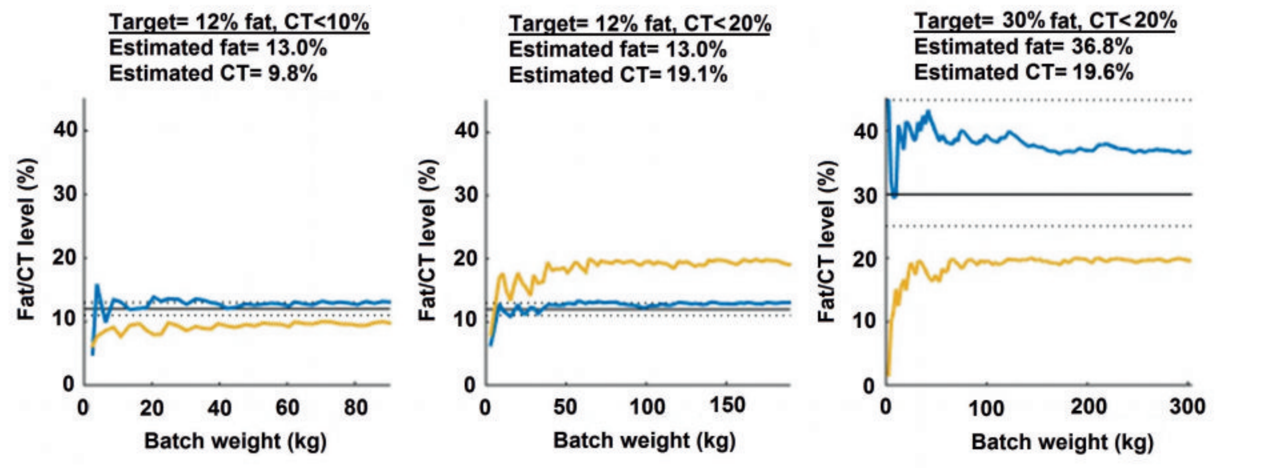

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Fig. 4: Evolving fat and CT content as function of batch weight for one sorting process from Example 4. The blue and yellow lines represent estimated fat and CT content respectively, while the dotted lines show the upper and lower limits for fat.

■ Optimize use of raw materials

Example 2 shows how different requirements for different batches can be used to make the system more robust towards changes in raw material streams. If one of the categories has loose boundaries, the other batches will be close to target even if the raw material changes. Having loose boundaries also minimizes the amount of meat that is not sorted.

■ Improve meat quality

Currently, sorting of meat trimmings in industry is mainly done by individual qualified operators (butchers). The batches are checked afterwards, and standardized (adjusted with fatter or leaner meat) if necessary. The standardization step requires grinding the meat and measuring subsamples in the laboratory. On-line estimation of fat content can replace this standardization, which removes the need for grinding. Thereby, increased water holding capacity of the trimmings will positively influence production yield and drip-loss at the retail stage.

■ Get the correct price

The price is often directly connected to the fat content, and with this system it is possible to get a precise estimation of the fat without standardization.

■ Optimize the selection of the cutting patterns

The system can be used to obtain improved and more accurate yield estimate models for cutting patterns, which again is an indirect stimulation to rationalization and cost reduction.

■ Adjust production according to orders and demands

This will increase profitability and reduce risk in the cutting line. Example 3 shows how additional restrictions can be used to steer the production in terms of final weight of the batches. It is therefore possible to change both the target values and the volume according to the market demand. The targets and restrictions must of course match the raw material at hand to some extent, but it is possible to make the system tilt towards upper or lower fat boundaries in order to increase the volume.

A slight drawback with the system presented is the moderate but systematic deviation between true and estimated fat, which is caused by the fact that the NIR sensor does not probe the entire sample. Chopping of the trimmings into smaller pieces improved the measurement accuracy at trimming level compared to Måge et al. (2013) and did also improve the target match and fat estimate accuracy of the resulting batches. The sorting system can of course be used with an X-ray system instead, if more accurate fat estimates are obtained with these systems. With more accurate trimming estimates, the deviation will approach zero, and the systematic under-estimation of low-fat batches and over-estimation of high-fat batches will be removed. In that case, the deviations from target will mainly be due to divergence between raw material stream and target values and other restrictions.

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