On-line sorting of meat trimmings into targeted fat categories

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Abstract

A system for on-line sorting of meat trimmings into categories with different fat levels was developed and tested by simulations and pilot-plant trials. The system consists of a conveyor belt, a NIR imaging scanner (QV500, Tomra Sorting Solutions, Asker, Norway), a flow weigher and grader (both Marel hf, Iceland) and a host computer containing synchronizing software and a sorting algorithm. The sorting algorithm is based on *desirability functions*, which makes it flexible when it comes to selecting number of categories, target values, limits for deviations and other restrictions. The results showed that the sorting algorithm works when the fat measurements are accurate, giving deviations from target lower than the selected ±1 percentage point limits. In reality there are some inaccuracies in the on-line fat measurements due to inhomogeneous meat trimmings. This leads to a systematic under-estimation of the fat percentage in low-fat categories and over-estimation in the high-fat categories. These biases can be reduced by e.g. improving the on-line fat measurement technology. However, simulations showed that the bias for either category was generally low (below 2 percentage points) and the current system therefore has potential for on-line implementation.

1 Introduction

In all abattoirs, most operations along the production line rely on manual handling or decision making to some extent. After manual extraction of high value parts of the carcass, a significant part of the meat, hereafter called trimmings, is separated into typically 2 or 3 classes of meat, according to fat content. Generally, there is a great difference in the value of the different fat classes, with the lean meat in the high cost end and the fat in the low cost end. Thus, it is economically beneficial to be as close as possible to the target fat value. The fat content of these classes is normally estimated using a combination of visual inspection and anatomical location. For improved process control, the trimmings are in many cases ground to enable instrumental fat determination and then standardised upon further processing. In order to minimise the number of processing steps and handling of the raw material, for the purpose of optimising the technical quality of the meat, it is of great interest to the industry to be able to analyse, sort and standardise the trimmings without grinding the meat.

Meat trimmings are highly heterogeneous, they vary in size, shape, chemical composition and structure. On-line estimation of fat content in single trimmings is therefore challenging. To obtain as representative measurements as possible, it is desirable to measure as large a part of the sample as possible. X-ray systems have been introduced for determination of fat in single trimmings (for example SensorX by Marel hf, Iceland). An advantage of X-rays is that the measurements are done in transmission so that the entire volume of the meat is sampled. This enables precise fat estimates (±1 percentage point, www.marel.com) for heterogeneous materials. Near-infrared spectroscopy (NIR) is another technology, which is a rapid, versatile and robust tool for online fat analysis. With NIR it is not possible to measure through meat cuts of greater thicknesses than 20-30 mm. There is, however, instrumentation on the market that can give spectral images of the whole surface, where the surface is representative of approximately the top 15-20 mm of the sample. The technology is based on a NIR imaging scanner, and the measurement principle used is contact-free interactance. The instrument was originally developed for moisture determination in dried salted cod (Wold et al. 2006), and has been used for a variety of applications in the food industry (O'Farrell et al. 2010; Segtnan et al. 2009; Wold et al. 2010, 2011).

A wide range of automatic grading systems have been developed for fruits and vegetables (Kondo 2010), where the objective usually is to detect and remove defect objects. Similar automatic grading systems based on imaging technologies can be found in the fish industry, where grading can be done according to e.g. colour, blood spots, bones and foreign objects (Mathiassen et al. 2011). An on-line inspection system has also been developed for separating wholesome from questionable poultry carcasses (Chao et al. 2002). All these systems are based on some kind of classification algorithm where the assignment of one object is independent of all the other objects. The systems therefore differ considerably from the application described here, where the objective is to create classes with different target values of a continuous parameter (fat percentage in this case). The assignment of each object thereby depends on all the other objects that have already been sorted. Some relevant classification algorithms based on predicted end-product quality have been developed by Berget et al. (2002a, 2002b, 2003), but to our knowledge no such systems are commercially available or have been tested on-line.

The main objectives of this work were to

- Develop an algorithm for on-line sorting of meat trimmings into categories with different fat contents
- Test the algorithm by simulations
- Test the complete sorting system in a pilot-plant environment

2 Materials and methods

2.1 Overall system

The system consists of a conveyor belt, a NIR imaging scanner (QV500, Tomra Sorting Solutions, Asker, Norway), a flow weigher and grader (both Marel hf, Iceland) and a host computer containing synchronizing software and a sorting algorithm. A schematic illustration of the system is given in Figure 1. The fat content of each trimming is predicted from the NIR scan, and combined with the weight measurement. The grader automatically directs each piece to a specific category based on results from the sorting algorithm. The number of categories and their target fat values are specified by the user.

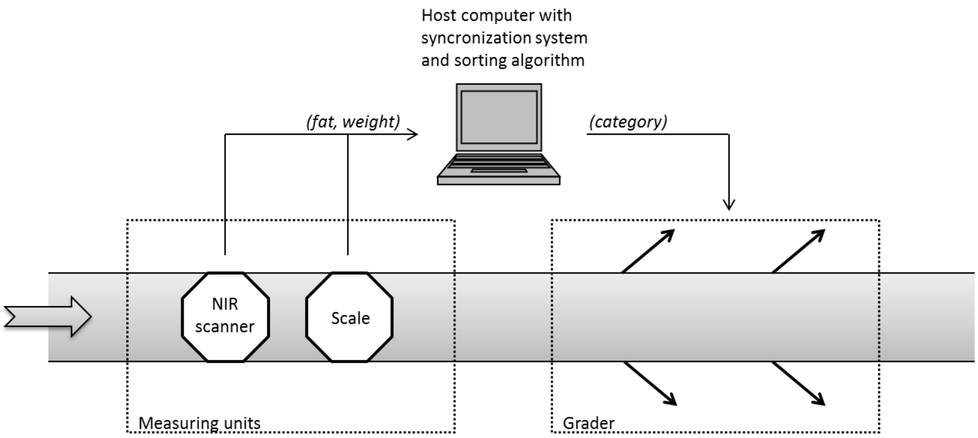

Figure 1: Schematic representation of the sorting system

2.2 Sorting algorithm

2.2.1 Multi-response optimisation

The sorting can be viewed as a multi-response optimisation problem, where fat content in each category are the responses. If there are N categories, there are N responses to be optimised:

$$\begin{aligned}
&\mathrm{Y}_1 = \text{Fat content in category 1, with target value } \mathrm{T}_1 \\
&\mathrm{Y}_2 = \text{Fat content in category 2, with target value } \mathrm{T}_2 \\
&\ldots \\
&\mathrm{Y}_\mathrm{N} = \text{Fat content in category N, with target value } \mathrm{T}_\mathrm{N}
\end{aligned}$$

Multi-response optimisation problems can be solved by using *desirability functions* (Harrington, 1965). A desirability function transforms each response to a dimensionless number d_i, interpreted as the desirability of the response value. The desirability d_i varies between 0 and 1. When d_i is 0, the solution is not acceptable, and when it is 1 the solution is perfect. The overall desirability of a system with *i* responses is defined as the geometrical mean of all d_i's:

$$D = (d_1 * d_2 * ... * d_N)^{1/N} \tag{1}$$

The objective is then to maximise D. The geometrical mean will be close to zero if one of the d_i's is close to zero, which means that a solution where all responses are "pretty good" will be preferred over a solution where some responses are perfectly on target and some are far from target.

The d_i functions are tailor-made for each specific problem to be solved. If the responses have target values, as they do in this case, the following formulation introduced by Derringer and Suich (1980) is often used:

$$d = \begin{cases} \left(\dfrac{y-L}{T-L}\right)^s, & L \le y \le T \\ \left(\dfrac{U-y}{U-T}\right)^t, & T < y \le U \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

Where T is the target value, U and L are upper and lower limits, and s and t define steepness on each side of the target T. Note that the target value T is not necessarily the mean value of U and L, and the steepness are not necessarily equal on both sides of T. Figure 2 shows how the steepness varies as a function of s and t. High s and t means that only values very close to the target are acceptable, while low s and t means that most solutions are equally good as long as they are within the lower and upper limits. s=t=1 yields a function where the desirability decreases linearly with the distance from target. Different responses can have functions with different steepness, which means that the steepness can be used to prioritize between responses.

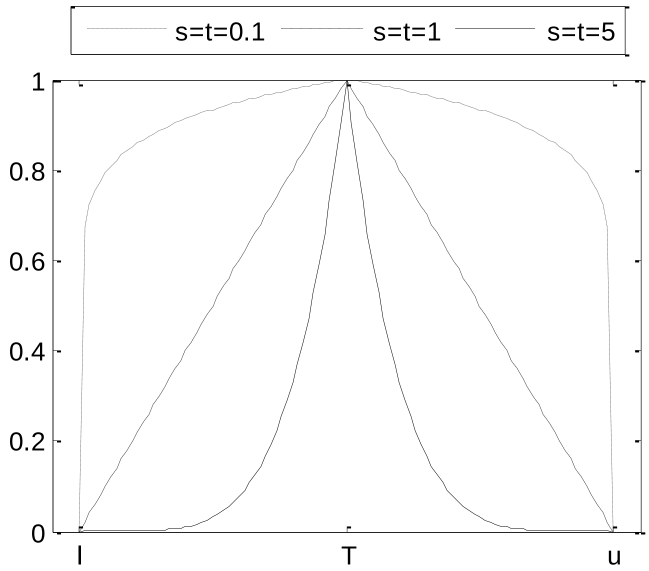

Figure 2: The plot shows how the steepness of a desirability function varies with the parameters s and t.

In the sorting algorithm, the overall desirability D is calculated for all possible outcomes. If there are three categories, the algorithmic steps are:

For each new meat piece:

1. Calculate the overall desirability D if the meat piece is added to category 1
2. Calculate the overall desirability D if the meat piece is added to category 2
3. Calculate the overall desirability D if the meat piece is added to category 3
4. Choose the category which leads to the highest D value
5. Update the content of the chosen category

If the overall desirability is zero for all three possible solutions, the meat is assigned to a fourth "unsorted" category. Trimmings that are unsorted can be recycled to the conveyor belt as they might fit in at a later stage of sorting.

2.2.2 Additional restrictions

The framework based on desirability functions is very flexible, meaning that it is easy to add more responses/restrictions to some or all categories. An additional restriction that will be tested here is to set limitations on fat content for each individual trimming in one or several categories. This is for example relevant for the low-fat categories, where one does not want chunks of pure fat even if it doesn't affect the average fat level. Likewise, it is not desirable to have too lean pieces in the high-fat category since lean meat is more valuable than fat.

In general, a separate desirability function is defined for each additional restriction. The desirability for a given category *i* is then the geometrical mean of all *P* desirabilities related to that category:

$$d_i = (d_{i1} * d_{i2} * ... * d_{iP})^{1/P} \quad (3)$$

2.2.3 Starting conditions

Many trimmings will be assigned to the “unsorted” category in the beginning, when each sample has a large influence on the average values. The fat level in a single trimming has to be very close to target in order to be assigned to an empty category. This means that a lot of pieces that would fit the category at a later stage, are discarded or assigned to another category which is not empty and thereby more robust towards changes. This problem is solved by adding e.g. 20 kg of “virtual” meat in each category at start-up, with fat level exactly at target. This will make the start more robust. The batch might be outside the allowed boundaries in the beginning, but this evens out when the total weight increases.

2.3 Software and implementation

The sorting algorithm was implemented in the commercial software package MATLAB (version 7.13, The MathWorks Inc., 2011), and the synchronizing software was written in C# (version 4.0, Microsoft Corporation, 2010) with a bridge towards the MATLAB-implemented algorithm.

All data were analysed and plotted in either MATLAB or Minitab 16 Statistical Software (Minitab, Inc., 2010).

2.4 Simulation tests

The sorting algorithm was tested using measurements of real beef trimmings by the NIR scanner QV500. The measurements were done in a Norwegian meat processing plant under ordinary production conditions. The trimmings passed under the scanner on a conveyor belt. The scanner was calibrated to produce one fat estimate per trimming. Details on the scanner and how it was calibrated is published by Wold et al. (2011). A total of 132 trimmings were weighed and then scanned two, three or four times from different orientations, mimicking the random variation that would occur in a processing line. Each scan produced one fat estimate. Each trimming was then homogenized and fat reference measurements were taken using low field proton nuclear magnetic resonance (NMR), using the Maran Ultra Resonance 0.5 tesla (Oxford Instruments, UK) (Wold et al., 2011). The total data set consists of 371 sample combinations of weight, predicted fat and true fat. The correlation between predicted fat (measured by the scanner) and the true fat is shown in Figure 3. It can be seen that there were quite large deviations between the two, especially for fat percentages higher than about 20. These deviations are mainly due to the heterogeneity of the trimmings. The correspondence between fat and weight is also illustrated in Figure 3. In the simulations, trimmings were selected randomly (with replacement) from these 371 samples until the desired number of trimmings was obtained.

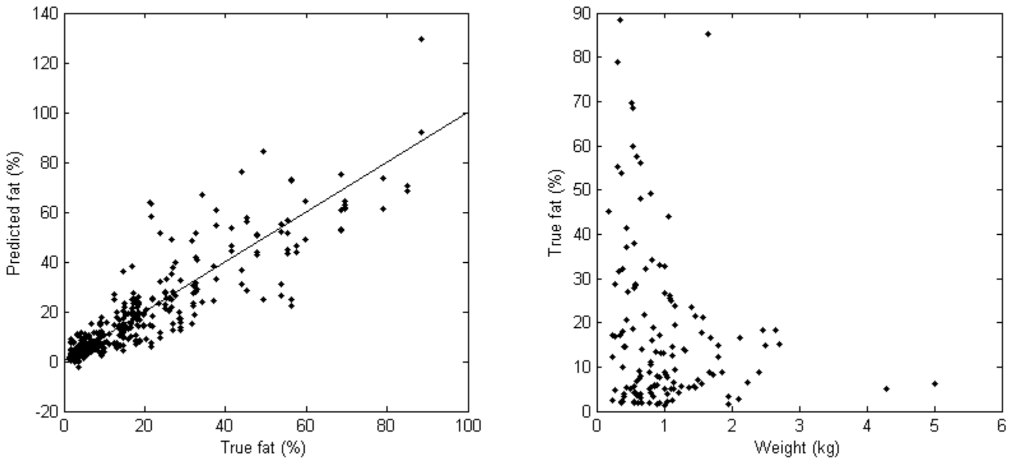

Figure 1 Data used for simulations. The left plot shows correlation between predicted and true fat, and the right plot shows weight versus true fat.

Two parameters were varied in the simulation tests: batch size and additional restrictions. They were varied according to a factorial two-level design, meaning that there were $2^2=4$ different combinations of settings. Each of the four combinations was repeated 50 times with a random selection of trimmings, in order to obtain reliable ranges of variation. The target values and limits were chosen to reflect realistic industry applications, and the same settings were to be used in the pilot plant tests with beef trimmings. The steepness parameter for the desirability function was set to five for all categories, implying that it was important to stay close to the target value for all of them. All parameters (both variable and constant) are summarised in Table 1.

Table 1 Simulation settings

	Level 1	Level 2
Batch size (# trimmings)	200	1000
Additional restrictions on single trimmings	No	All trimmings should be: >18 fat% in the 21%-category <8 fat% in the 5%-category
Target values (mean fat%)	$T_1=5$, $T_2=14$, $T_3=21$	
Dummy start weight	20 kg in each category	
Steepness of desirability function	s=t=5 for all categories	
Upper and lower levels for desirability function	$U_i=T_i+1$ $L_i=T_i-1$	
Number of repetitions for each combination of settings	50	

2.5 Pilot plant trials

Five batches of pork (A-E) and three batches of beef (F-H) trimmings were collected, with total weights varying from 104-189 kg. The pork batches were sorted into three categories with target values 6%, 14% and 23% fat, and no restrictions were added in the sorting algorithm. After sorting, each category was run through the NIR scanner (without sorting) three times, in order to get an estimate of the fat content. After the third rerun all batches (except E) were ground thoroughly. Three samples of three kg each were collected from the ground samples, then homogenized, and the fat content in one subsample from each of these were determined using a Foss Foodscan system (FOSS, Hillerød, Denmark). The experimental steps are illustrated in Figure 4.

The three beef batches were sorted in a similar manner, with target values 5%, 14% and 21% fat. This time, *two* subsamples were taken for fat reference measurements from each homogenized sample. In addition, restrictions were imposed on batch G and H. The restrictions were the same as in the simulations, see Table 1.

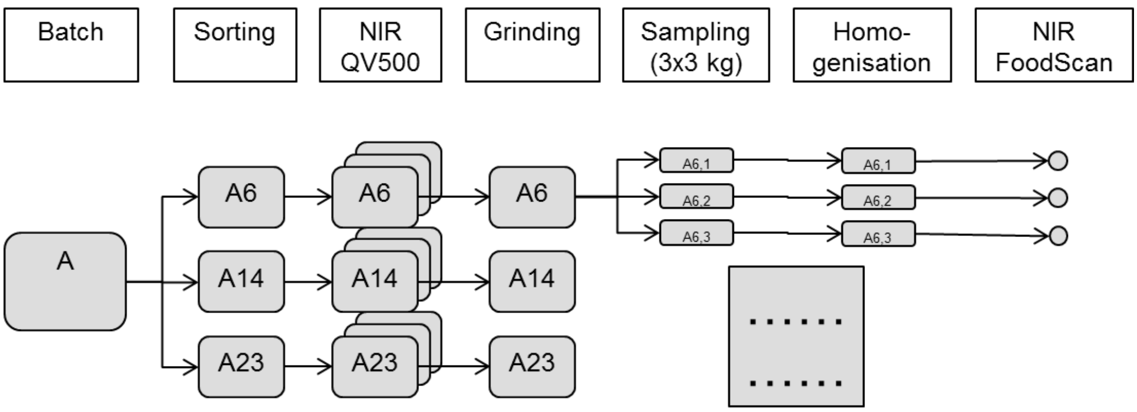

Figure 4: Experimental steps for sorting pork in the pilot plant

3 Results

3.1 Simulations

As an example, one of the simulated sorting processes will be presented in detail. The selected simulation had no additional restrictions, and the batch size was set to 200 trimmings which led to a total weight of 203 kg. The sorting process is illustrated in Figure 5. The 5% category contains 75 kg after the sorting is finished. The estimated fat level is around four percentage points too high at the beginning of the process. This is due to the fact that the algorithm starts with a virtual 20 kg of meat, in order to avoid many rejections in the beginning of the sorting. These 20 kg are used when calculating the desirability value, but do not contribute to the estimated fat level in Figure . However, the average fat percentage slowly decreases towards a final estimated value of 5.9. The true fat level is slightly higher throughout the process, and ends up 1.2 percentage points above the target. The 14% category receives only a total of 23 kg, and both the estimated and true fat is very close to target during the entire process. The 21% category is the largest (105 kg), but both the estimated and true fat level is relatively stable after approximately 30 kg. The deviation between estimated and true fat is largest for this category. While the estimated value is very close to target, the true fat content is consistently about two percentage points lower than target.

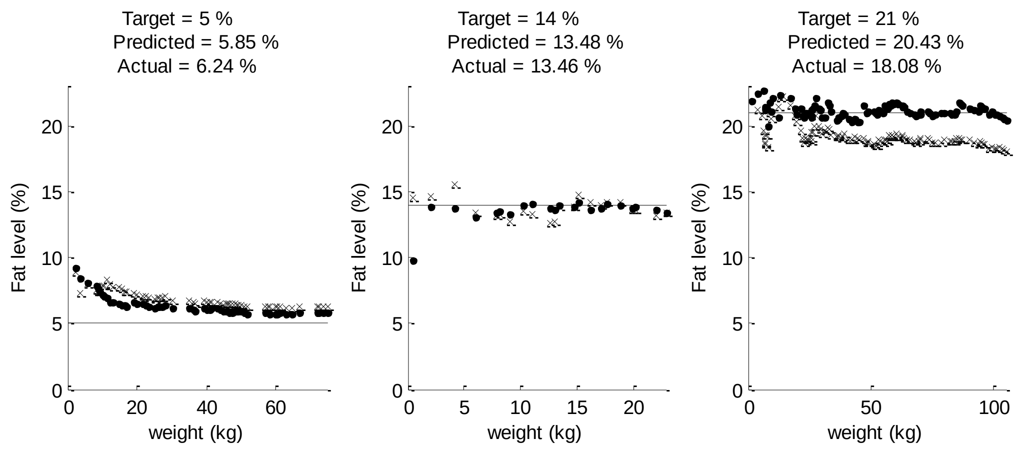

Figure 5: Evolution of the sorting process for a selected simulation. The abscissa shows total weight in each category, and the ordinate shows average fat content. Dots and crosses represent estimated and true fat values respectively. The numbers above the plot are the final values when all trimmings are sorted.

Fifty random repetitions were simulated for each of the four combinations of batch size and restriction. The resulting deviations between target values and estimated and true values are given in Figure 6. It is clear that the main difference between batch sizes is lower variation for the larger batches. This indicates that the system has not always reached a steady state when the batch size is small, but the overall results (which will be described next) are the same irrespective of batch size. Since the large batch size is more consistent, we choose to focus on those results when evaluating difference between categories and restrictions.

Figure 6 shows that while the estimated fat-value is generally within ±1 percentage point (which were set as the upper and lower limits), the true value is in some cases more than ±2 percentage points off target. When no additional restriction is defined, the 5% category is always under-estimated; the 14% category is very close to target, while the 21% category is always over-estimated. When adding the restriction on each trimming in the 5% and 21% categories, the deviations decrease for these categories, while the 14% category now becomes 1-2 percentage points below target.

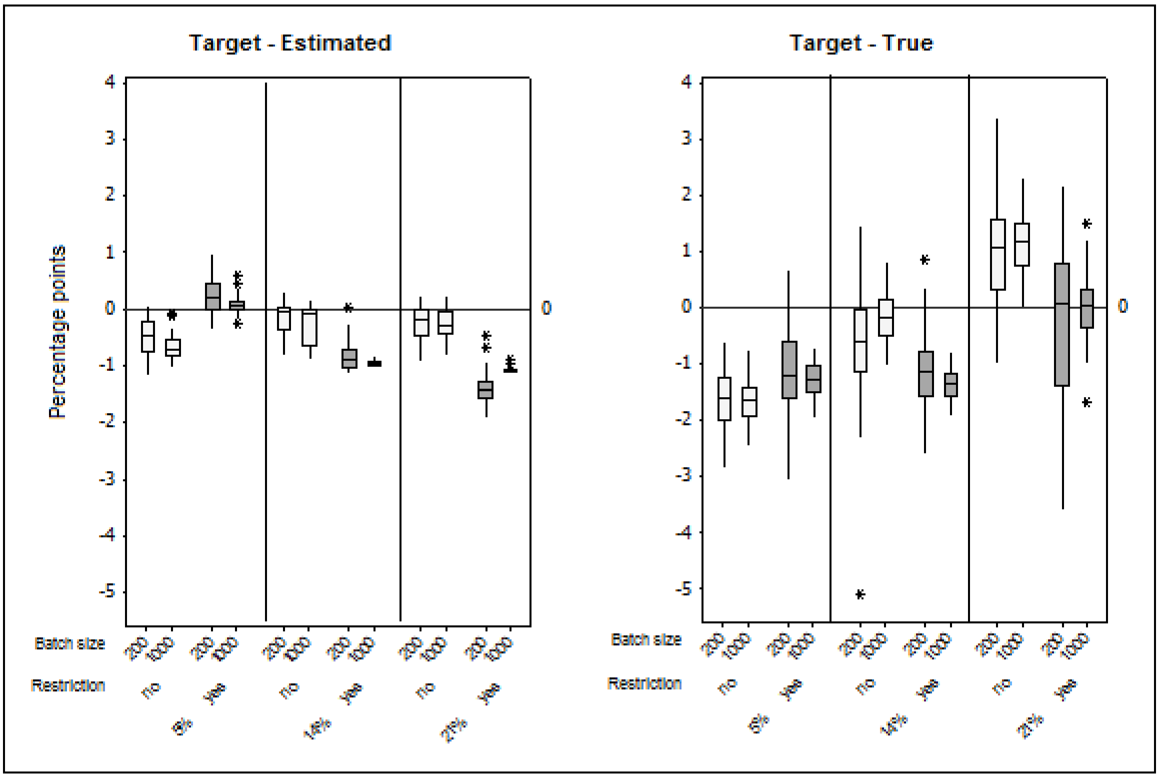

Figure 6: Boxplot showing the deviation between target value and estimated fat content (left) and true fat content (right) for each category and simulation setting.

The batch weights for 200 and 1000 trimmings across all replicates were 176.4 ± 17.1 kg and 863.7 ± 96.3 kg respectively. Figure 7 shows the relative amounts of meat ending up in the different categories. When no restriction is added, around half of the meat is directed to the 21% category, while the remaining half is distributed almost evenly between the 5% and 14% categories. Adding the restriction induces a dramatic change in this distribution. More than half of the meat is now sorted into the 14% category, while only one fifth goes to the 21% category. The amount of the batch allocated to the 5%-category stays approximately the same.

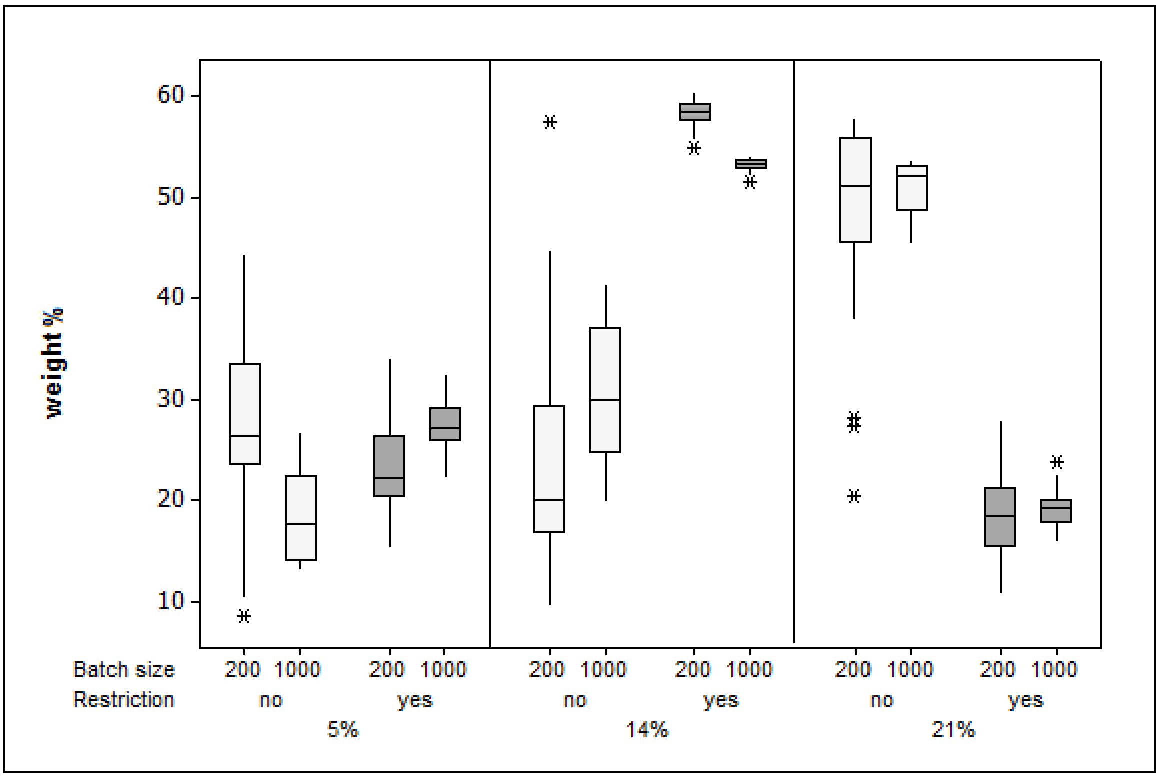

Figure 7: Boxplot showing the percentage of total batch weight received by each category for different batch sizes and restrictions

The number of unsorted trimmings is highly affected by the added restrictions, as expected. For the 200-sample batches, weight% of unsorted trimmings increases from 3.9(±1.6) to 15.0(±4.6). For the 1000-sample batches, the corresponding increase was from 1.7(±0.6) to 17.6(±2.0).

3.2 Pilot plant

All results for the pilot plant trials are given in Table 2. Five batches of pork (A-E) were sorted into three categories with target values 6, 14 and 23% fat. All batches were run without any additional restrictions, and the resulting fat estimates for each category is plotted in Figure 9 (upper panel). The reference measurements and NIR scans both show the same pattern as the simulations; the low-fat category contains slightly too much fat, and the high-fat category contains too little fat.

Three batches of beef were sorted into three categories with target values 5, 14 and 21% fat. The first batch (F) was run without restrictions, while batch G and H were subjected to the same restrictions as in the simulation study (see Table 1). The summarised results for all three batches are plotted in the lower panel of Figure 9. There is a discrepancy between the NIR scans and reference method for the 14% and 21% categories; the reference method shows consistently 2-4 percentage points lower value than the NIR scans. The reason for this is not known, but it might be due to a bias in the NIR prediction model for high-fat beef trimmings.

The evolvement of batch H is shown in Figure 8. The 5% category is estimated to 4% by the algorithm, which is the lower acceptable limit according to the desirability function. The estimate is not able to reach target value since high-fat trimmings are not allowed, but as low-fat batches generally are under-estimated the true value is still slightly above target. The 14%-category is over-estimated, as the simulations also showed, while the reference values are lower than those estimated by the algorithm. The 21%-category is also over-estimated, which is expected since low-fat trimmings are not allowed due to the added restrictions to beef trials. The reference values are however closer to target.

Adding restrictions led to the same change in yield for each category as was seen in the simulations: The 5% category received approx. 35 weight% regardless of restrictions; the 14% category increased from 25 weight% to 55 weight%, and the 21% category decreased from 42 weight% to 8 weight% of the total batch weight (see Table 2). In the meat industry, the need for meat with 14% fat is greater than that of 23% fat, indicating a benefit of using such restrictions. The amount of unsorted trimmings was unfortunately only measured for batch H, where 12.4 weight% was not assigned to any category. All these results indicate that the data used for simulations were quite representative for the beef trimmings in the pilot trial.

Table 2 Overview of the pilot plant trials.

		Restr.[1]	Day	Target	Alg[2] (%)	Scan[3] (%)	Ref[4] (%)	Weight (kg)	Weight (weight%)	Total weight (kg)
Pork	A	No	1	6%	7.2	10.0 ± 0.6	10.8 ± 1.5	63.4	33.6	188.8
				14%	14.0	15.5 ± 0.5	15.1 ± 0.8	103.9	55.0	
				23%	22.9	18.9 ± 0.8	23.0 ± 0.8	21.5	11.4	
	B	No	1	6%	6.1	7.4 ± 0.5	9.9 ± 0.6	39.1	22.1	176.7
				14%	14.0	13.8 ± 0.3	17.0 ± 1.8	90.6	51.3	
				23%	23.0	19.8 ± 0.8	21.5 ± 0.3	47.0	26.6	
	C	No	2	6%	6.4	9.2 ± 0.5	9.3 ± 0.4	76.5	44.8	170.7
				14%	14	12.3 ± 0.7	15.0 ± 1.8	32.1	18.8	
				23%	23.1	17.8 ± 1.1	17.0 ± 2.0	62.0	36.3	
	D	No	2	6%	6.4	9.8 ± 0.54	8.9 ± 1.4	62.2	40.3	154.4
				14%	14	16.2 ± 0.9	16.6 ± 1.7	28.5	18.5	
				23%	23	18.6 ± 1.8	19.2 ± 1.2	63.7	41.2	
	E	No	2	6%	6.3	8.0 ± 0.5	*	56.4	54.1	104.3
				14%	14	16.1 ± 0.6	*	23.2	22.2	
				23%	23	17.9 ± 1.6	*	24.7	23.7	
Beef	F	No	3	5%	5	8.4 ± 0.4	7.2 ± 0.7	51.2	32.6	157.0
				14%	14	15.8 ± 1.1	12.2 ± 1.1	39.6	25.2	
				21%	21	23.2 ± 1.4	18.2 ± 1.7	66.2	42.2	
	G	Yes	3	5%	3.7	6.3 ± 0.5	6.7 ± 0.8	55.1	37.0	148.9
				14%	14.8	17.9 ± 0.3	14.2 ± 0.5	81.4	54.7	
				21%	23.1	23.6 ± 3.0	20.6 ± 1.1	12.4	8.3	
	H	Yes	3	5%	4	5.7 ± 0.4	5.9 ± 0.3	54.7	35.8	152.6
				14%	15.1	14.9 ± 0.4	12.0 ± 0.9	84.4	55.3	
				21%	23.4	20.8 ± 2.3	17.4 ± 1.5	13.5	8.8	

[1]Whether or not additional restrictions were imposed, see Table 1 for details.
[2]Average fat content as calculated by the sorting algorithm.
[3]Average fat content as predicted by reruns through the NIR scanner ± standard deviation of replicates.
[4]Average fat as content measured by reference measurement ± standard deviation of replicates.

4 Discussion

With the current system, there will always be a systematic under-estimation of low-fat categories and a corresponding over-estimation of high-fat categories. This is due to non-random heterogeneity in the trimmings; many pieces are lean on one side and fat on the other side, and the fat content predicted by the NIR scanner depends on which side is scanned. A trimming which is predicted to be lean, and thereby sorted into the low-fat category, will sometimes have a true fat-level which is much higher. The true value will however never be much lower, and this leads to the systematic bias observed in simulations and pilot plant trials. Solutions to this problem could be to:

- use a measurement system that gives more accurate fat estimates per trimming. For the NIR system this can be obtained by scanning each trimming from more orientations, in order to obtain a more representative fat value. This involves either a new scanner design or a conveyor system that flips and re-scans the trimmings
- re-scan each category after sorting, as was done in the pilot plant trials. This gives a more reliable estimate, and the fat content can be adjusted afterwards. This solution is more labour intensive, but can also be done automatically and continuous if several NIR scanners are available
- set the target values correspondingly lower for the low-fat categories and higher for the high-fat categories. This is not straight-forward, as the magnitude of the bias will depend on the distribution of trimmings as well as the target value itself. It is impossible to make general recommendations on how to specify the target values

Despite of the observed biases, the automatic sorting system has a commercial potential. The different batches can be standardised according to fat contents without the need for a grinding step, which improves the quality of the meat upon further processing, and reduces handling and labour costs.

The fractions of meat sorted into the different categories when using restrictions were in this case more favourable to the industry, since there is a higher demand for the 14% category than the 23% category. Generally, these fractions will also depend on the meat itself; trimmings from lean animals will give a higher proportion of the low-fat categories etc. It is often desirable to control the amount to each category, depending on price and demand. To do so in a more controlled way than using restrictions, it is possible to add a desirability function for the weight distribution itself in order to steer the production in the right direction.

In some meat batches it is also important to keep the connective tissue below certain boundaries. For example, in Norway the ratio of connective tissue and protein should be below 0.05 for the 5% category of beef. If connective tissue could be predicted by e.g. a modified NIR scanner, this restriction can easily be incorporated in the sorting algorithm by adding more desirability functions, as described in the theory section.

When adding more restrictions, it is important to tune the steepness parameters of the desirability functions correctly. The steepness should depend on the importance of each restriction, and in this setting it is natural to define the steepest desirability function for the fat content. It is also important to acknowledge that the more restrictions we add, the harder it will be to obtain the desired fat level within a set tolerance, and the more pieces will be discarded by the algorithm.

5 Conclusion

A system for sorting meat trimmings into categories with different fat levels was developed and tested. The sorting algorithm is based on desirability functions, which makes it versatile when it comes to definition of categories, additional restrictions and prioritising between categories and restrictions. The system was tested both by simulations and pilot-plant trials. The results showed that the sorting algorithm is able to create batches of meat with fat% within the defined tolerance limits, and that the total system has potential for industry implementation. The major drawback of the system is inaccuracies in on-line fat measurements of meat trimmings, which lead to a systematic (although small) bias for the low-fat and high-fat categories.

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