final report

Project code: A.TEC.0064

Prepared by: Paul Hosen
Nortura

Date published: June 2009

ISBN: [MLA to provide]

PUBLISHED BY

Meat & Livestock Australia Limited
Locked Bag 991
NORTH SYDNEY NSW 2059

CL measurement using NIR Technology

Meat & Livestock Australia acknowledges the matching funds provided by the Australian Government to support the research and development detailed in this publication.

partner
logo

Abstract

The Australian meat sector requires an online lower cost measurement solution for CL QVision, using Near Infra Red (NRI) technology developed in Norway, shows potential and has been the subject of evaluation in this MLA study with Nortura. The project has produced good calibration models for fat content in beef trimmings (R=0.98, RMSEP=2.8%). The fat model applied on 43 single trimmings with average fat content ranging from 1.6 to 49.3% fat, gave an RMSEP =8.7%. Simulations based on fat estimates in single trimmings indicate that the prediction error decreases with batch size, and already for batches of 20 Kg the RMSEP is as low as 1.5%. In summary, the NIR scanner can give reliable and accurate fat estimates of batches of beef trimmings, including when the batches are quite small. For the concept to work properly it is a requirement that the trimming or layers of trimmings on the belt are not too thick. In this study maximum thickness was 80 mm. It is expected that a follow up project, with matched MLA funding, expands the trials and delivers an automated solution for CL measurements and product sorting in a Nortra plant followed by the same in an Australian plant.

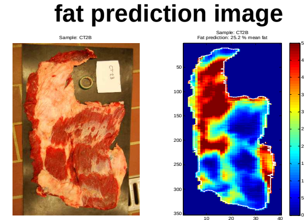
Executive Summary

QVision, developed in Norway uses Near Infra Red (NRI) technology to measure CL in trimmings and meat pieces after a beef deboning line. The work contracted under the MLA and AMPC project relating to CL measurements has provided encouraging results as the tests show consistency and good accuracy. The trials and structured test have been conducted at the Nortura plant in Trondheim, Norway.

Good calibration models for fat content in beef trimmings (R=0.98, RMSEP=2.8%) have been produced. The developed model can be used on single pixels to get a picture of fat distribution, or it can be used on the average spectrum from each trimming/portion of trimmings. In the tests conducted the latter approach was used. An acceptable fat calibration was also obtained for frozen calibration samples, with somewhat higher prediction error (R=0.96, RMSEP=5.6%). Each sample was scanned twice compared to the fresh samples, which were scanned six times. The result is promising, and it may be assume that a reliable model for frozen blocks is also a likely outcome. The fat model applied on 43 single trimmings with average fat content ranging from 1.6-49.3% fat, resulted in a rather high RMSEP (8.7%) and a correlation of 0.84. This was expected, as the heterogeneity of the trimmings affects the measurements. High prediction errors for fat/heterogeneous samples have been observed; but lower errors for lean samples. Three samples gave spectra that did not fit into the calibration model. These were lean samples, while the fat estimates were very high. Optical signals were very weak from these samples, and spectral shape slightly different from the others. As yet, the reason for these deviations is not known. It is suspected that the structure of the meat might have played a role. Further effort should be used to investigate the deviations that may be caused by the structure of the meat producing models that can be made satisfactorily into a future calibration. **Simulations based on fat estimates in single trimmings indicate that the prediction error decreases with batch size, and already for batches of 20 Kg the RMSEP is as low as 1.5%.Test measurements on true batches in the range of 10 – 24Kg verifies this result with an obtained RMSEP of 1.33%. Simulations with varying batches indicate again that the RMSEP decreases with increasing batch size and, for the present case, reaches about 0.6% for 100 Kg batches, which** should be sufficient. A test with the QVision scanner using 3 big batches of 145, 164, and 170 Kg gave the same fat estimates as the inline microwave system on ground meat.

In summary, the NIR scanner can give reliable and accurate fat estimates of batches of beef trimmings, including when the batches are quite small. The proven concept should be applicable to the on-line estimation of fat in trimmings in order to determine the batch fat content and also to control the formation batches to different target fat levels. For the concept to work properly it is a requirement that the trimming or layers of trimmings on the belt are not too thick. In this study maximum thickness was about 80 mm. Thicker trimmings might be used, but careful hardware adjustments might then be required.

Whiteness image and Photo and fat prediction image



Contents

1 Background

After the beef deboning process there is a requirement for fat-lean measurements of the resulting meat pieces in order to assemble recognisable meat pieces in specific quantities in weight that have a specified CL percentage.

The process of break up and deboning varies between different plants. In some plants the of grading for fat starts the end of the slaughter operation where each carcass is graded (Figure 1.1) for fat cover into a 85%, 90% 0r 95% band. Grouping of carcasses in these categories allows the de-boning operation to produce deboned meat from carcasses in the same bands of fat. The task after de-boning is to mix the resulting meat pieces or trimmings from the carcasses in the band to produce bulk pack cases of meat where each pack has the target lean content as that of the grade of the carcass. Clearly, this means that a judgement has to be applied after de-boning and trimming to assess the lean content of the resulting pieces and to bring boneless meat of different quantity and fat content to make up a pack that meets the target lean percentage.

Figure 1.1: Carcass grading

The plants visited in Australia use different practice to produce cases (generally 27.2 Kg or 60lb) weights of beef meat or trimmings at a certain CL value. Visits to Rockdale and Teys were made and observations and other plans have also been made. In general two practices were observed as in Figure 1.2.

Meat from boning, slicing and trimming stations travel on conveyors as A. Trimmings are all mixed before delivery to conveyor B where two practices follow. In first case at point C, Figure 1.2, manual sorting of pieces or trimmings takes place and the holding containers at C would have the CL category planed for the packing operation that follows at D. At D meat of the given CL is weight into the cases as shown giving the target weight and CL in the box. Labelling follows and the case is checked for CL using an X-ray system if this is available. In some plants the X-ray is a simple monitor and in others it is used to assist rework or re-labelling.

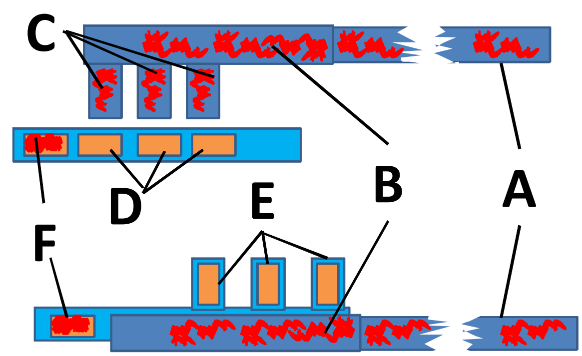


Figure 1.2: Two practices observed in

In the second case, point E of Figure 1.2, meat is picked manually and case packed at the same time as the meat is visually assessed for CL. The manual packing operation is expected to produce the target CL and weight. Finished cases at F continue to the X-ray or case closing and freezing or palletising.

In the observations, it is the judgement and the skill in blending of those with this responsibility that provides the consistency in achieving the target case lean percentage.

Figure 1.3: Lean measurement of finished cases

After blending, which is manual, each case is measured using an x-ray system in order to assess that the target lean ratio is met. Figure 1.3 shows the equipment and the resulting display with the measurements. Note that the actual lean content is set to be 1% below the target. Under the current manual process it is likely that the individual cases do not necessarily have the CL intended, however the measuring equipment averaging the data would show that the on the whole the cases have the target average. To this end, if the individual cases are to be at the target CL percentage, then alternative practices are required to measure the lean percentage of the deboned meat from different stages in boning room on line. With the combination of weight and lean information the process of mixing needs to be automated to give the precision to reach the target CL.

1.1 Requirement

The objective is to bring deboned meat and trimmings from various stations and to mix the meat in such manner that the cases of specific target weight are assembled with the target lean percentage of 85%, 90% or 95% CL ± 1% or better. Given that processers would optimise the lean content for maximum profitability, then the target would actually be 84%, 89% and 94% exact.

In the normal operation there may be several types of meat from multiple stations and the challenge of **meat handling** should not be underestimated. This study is not aiming to solve this particular issue of handling and weight control, but rather focus on the accuracy of measurement.

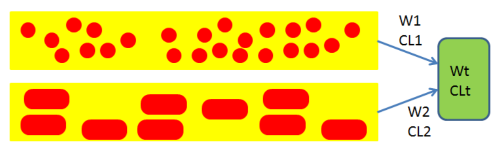


Figure 1.4: Objective is to achieve target weight Wt at target Lean CLt%.

With reference to Figure 1.4, an attempt is made to outline the future task in hand.

Assuming two conveyors of trimmed and deboned meat are travelling t constant speed bringing meat to a point of assembly where the weight of meat per unit of time on each conveyor is measures along with the fat content for the same weight per unit of time. W1 and CL1 say on conveyor with small pieces and W2 and CL2 for larger pieces (See Figure 1.4). The requirement is that measurements of W and CL on each conveyor with a process of controlled mixing of the correct ratio of the met weight, whilst taking the CL value into account the target Weight in the case at the desired CL is reached. Even in the simple case of this simple two conveyor system the challenge of handling process should not be underestimated as the CL1 and CL2 will vary in somewhat random fashion and the rate at which meat is delivered would also introduce a weight variability. Thus the handling of the meat in a controlled manner once the weight rate and the CL are measured becomes an important aspect of the process and needs to be part of the solution at a later date.

After visits to plants, it is also possible that 3 or 4 different categories of meat with different but target CL may be needed, whilst each of the categories of meat is separately handled at variable throughput or weight. This should emphasise the challenge of meat handling as a separate matter for the process of fixed weight fixed CL case packing.

Figure 1.5, illustrated the task in hand as follows with a simple example. The procedure needs to handle meat of different CL rating and unspecified weights from one or more conveyors X through QVision and sort the meat using a handling system post QVision to provide meat in containers that have the desired target CL as demanded by the production plan of the moment. Thus Y1, Y2 and Y3 need to have accurate CL for a given target weight. The main complication is that the meat weights of certain CL value do not arrive in a structured manner.

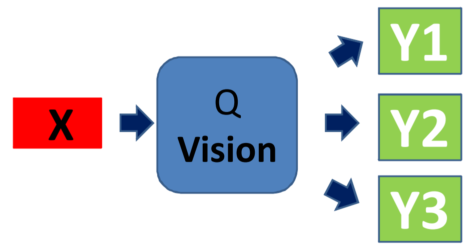


Figure 1.5: Example of target procedure.

For the present, the requirements form the intended Q-Vision test would be to perform a series of tests to show accuracy of the measurement. Although different approaches may be adopted, the closest to the operating process would be to measure the meat pieces and trimmings currently produced. Although the practices are different and given that at this stage the scope of the test does not include definition of the handling process for best integration of Q-Vision equipment not a typical operation, the form of the test can only be based on measurements of the meat types. This test has the objective to assess the accuracy of the CL measurement on different pieces as presented on conveyors.

2 Project Objectives

The main goal of this work has been to calibrate the Qmonitor system for fat measurements in beef trimmings and evaluate the performance on different kind of samples. The detailed objectives have been:

- Make a fat calibration that can be used on intact beef.
- Evaluate the model for single trimmings (maximum thickness 60 mm) and estimate the prediction accuracy for such samples.
- Evaluate the model for on-line estimation of fat content in batches of trimmings.
- Determine prediction accuracy as function of batch size.
- Develop fat calibration for frozen beef.
- Elucidate the possibility of detecting connective tissue (CT) with Qmonitor

3 Methodology

The work was divided in the following stages:

1. Collection of samples and spectral data at Nortura Tunga plant for calibration purposes
2. Reference measurements of fat in calibration samples
3. Establish on-line calibration for fat based on spectral data and fat measurements
4. Evaluate the model at Nortura Tunga plant, where batches of trimmings and single trimmings were measured.
5. Produce new fat reference measurements.

6. Produce final analysis of measurements including estimates of prediction accuracy for single trimmings and batches of varying size.
7. Perform scan and analysis of trimmings with high CT.

A more detailed description of the stages is given below, followed by results and discussion.

3.1 Collection of samples and spectral data at Nortura Tunga for calibration

The QVision scanner was installed in the production area at Tunga by Qvision AS. The equipment with a black conveyor belt was commissioned off-line adjacent to the cutting line. This allowed more flexibility when conducting tests.

Plastic frames (22×28×4 cm) were filled with small trimmings of beef. The frame samples were selected to span the relevant range of fat; from lean meat all the way close to 100% fatty tissue. Figure 3.1 shows examples of four calibration samples in crates. The meat in each crate was scanned 6 times. First, the top side was scanned, then, with the samples turned upside down, the bottom was scanned.

The trimmings were then mixed, the top and bottom were scanned again and this was repeated, resulting in 6 scans of the same material. The average of these 6 scans was assumed to be representative of the average fat content of the frame and was used in the calibration work. A total of 26 calibration samples/frames were measured.

Figure 3.1 Example of calibration samples in frames

After scanning the crates, the trimmings from each crate were placed on a plate covering about twice the area as the crate, making the samples about half the thickness (20-30 mm). These plates (Figure 3.2) were scanned twice, with the samples being mixed between the scans. The trimmings were then spread out on the belt as small irregular portions and were again scanned twice.

Finally the trimmings were placed back in the crates and placed in a freezer overnight. The frozen samples (Figure 3.3) were scanned twice, top and bottom faces.

Figure 3.2 Calibration samples placed and measured on conveyor belt.

Figure 3.3 Frozen calibration samples

Twenty five single trimmings were picked out for scanning. These were selected based on shape, thickness and heterogeneity in order to span relevant variation. Each trimming was scanned 2-3 times on different sides/positions. Figure 4 shows some of the trimmings. The thickness varied between 30 – 80 mm.

Figure 3.4 Some of the scanned single trimmings

3.2 Reference measurements of fat in calibration samples

All samples were frozen after the tests. Later, they were ground, homogenized, and 3-5 parallel sections were subjected to fat measurements. The fat measurements were done with a calibrated bench-top NMR low-field system, Maran Ultra (Resonance, UK). The average values of the parallel sections were used in the calibration work.

3.3 Establish on-line calibration for fat based on spectral data and fat measurements

There are several ways to calibrate an NIR imaging system. In this work, the mean NIR spectra from each of the calibration samples were extracted, and these were used to make a calibration against fat content. Multivariate regression (Partial Least Squares Regression, PLSR) was used to develop the calibrations. All calibrations were validated by either cross validation (leave-one-out) or specific test set.
Extraction of meat/muscle spectra from the multispectral images was automated to speed up the work and to allow use on-line in the scanner. A segmentation criterion for what is meat or fat was defined; then all pieces of meat on the conveyor were detected and the spectra extracted. Figure 3.5 shows an example for a frozen calibration sample and a single trimming.

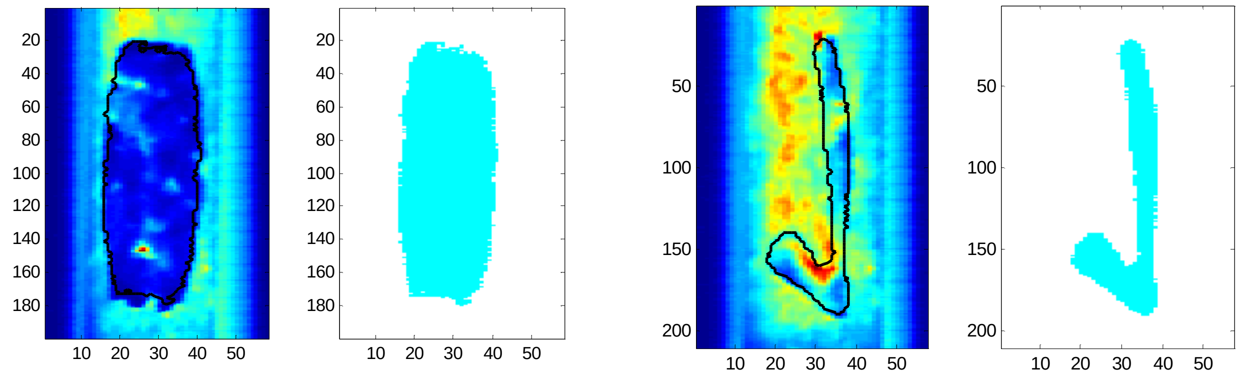


Figure 3.5 Scans and segmented meat from frozen calibration sample (left) and single trimming (right).

From each sample, an average absorption spectrum was obtained, and this contains quantitative information about fat, water and protein. The spectral shape is also affected by colour, optical properties, as well as distance from the scanner (thickness of meat).

To remove some of the spectral variation connected to variation in sample distance from the scanner it is common to pre-process the spectra in different ways. In this work done mainly used Standard Normal Variate (SNV); subtract the mean of the spectrum from each wavelength in the spectrum and divide by the standard deviation of the spectrum.

Figure 3.6 shows absorption spectra from the same samples before and after normalisation. To avoid the influence of sample colour variation, it is possible to omit the shortest wavelengths on the border between the NIR and visible region (typically, remove 760 – 840 nm).

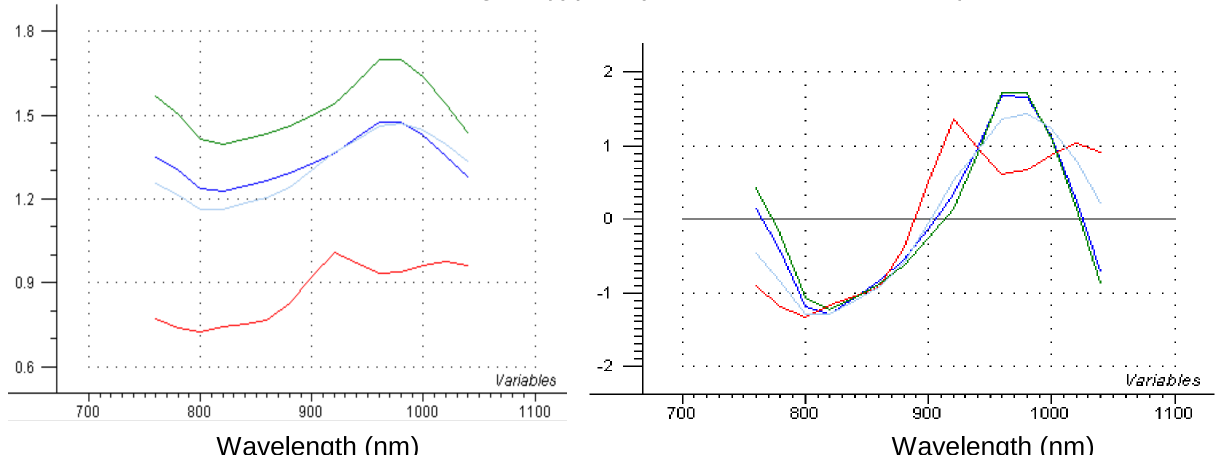


Figure 3.6 Absorption spectra (left) and SNV corrected spectra (right). Red spectrum is from very fat sample (82% fat), green is from lean sample (2.8% fat), and the others are in between.

Note that the peak at about 930 nm stems from fat, the broad peak at 980 nm is water, while the variation at the lower wavelengths is due to colour variations. The great offset differences in the absorption spectra are due to different factors, but mostly due to the increased light signal through white adipose tissue relative to that from darker lean meat. This results in higher absorbance for lean meat. In the SNV corrected spectra the variation connected to chemical composition is dominating the spectra, but features related to optical properties and sample size are still present to some extent.

3.4 Evaluation of the model where batches of trimmings and single trimmings were measured.

After modelling, the most appropriate model (see results below) was implemented in the scanner at the Nortura Tunga plant.

The work involved:

- Adjustment of optimal threshold criterion for segmentation of beef
- Insertion of the new regression vector
- Installation of an NIR sensor in reflection mode, in case the interactance signals from some samples was too low.

The second set of trials at Nortura Tunga plant was to evaluate the model on batches of intact trimmings as well as on single trimmings. Since the scanner introduces a limitation on how thick the intact trimmings can be, the thickness of some of the trimmings and meat cuts were reduced by cutting. Thickness of the trimmings varied by10 mm to 80 mm. The following tasks were performed:

3.4.1 Scanning of 3 big batches of approximately 160 kg.

Trimmings from these batches were scanned, one by one or as portions of around 2-3 Kg. Single trimmings were not thicker than 80 mm, but could vary to a reasonable degree in length and width. Some single trimmings weighted about 2 Kg. Every trimming or portion of trimmings was weighed immediately after scanning, and weight and estimated fat content were continuously entered into an Excel spreadsheet. After scanning a batch, the estimated fat content were immediately calculated. The batches were then ground and fat content was measured by an in-line microwave system connected to a grinding machine. This microwave system had recently been calibrated. It produces reliable results for batches of 200 Kg or more. Weights down to 100 Kg could be measured, but the procedure requires very careful control to ensure that the whole batch is measured properly.

From the 3 batches taken directly from the production line and two had 14% fat each and the third 21% fat. See photo below:

VEMA-trolleys with approximately 200 Kg batches of beef trimmings

3.4.2 Scanning of 13 20 Kg batches of beef trimmings

Nortura boxes were filled with trimmings amounting to about 20 Kg. These were scanned in the same way as the bigger batches. Batches with different fat content were formed by mixing lean and fat batches. After scanning, the batches were ground and the reduced size samples were collected for fat referencing. The reason for only scanning smaller batches of 20 kg, was that these batches can then be combined, to make larger batches, providing the basis for estimating accuracy for different batch sizes.

3.4.3 Scanning of another 20 single trimmings

20 single trimmings were scanned to increase the number of single trimmings tested, in order to get a better estimate of prediction accuracy. They were again scanned on 2 or 3 different sides, weighted, photographed, and checked by referencing.

3.4.4 Samples containing high connective tissue

The purpose was to scan these with both the NIR and VIS modules to see if it is possible to detect the connective tissue and distinguish it from fat and muscle.

3.5 New fat reference measurements

The newly collected samples/ground samples in the form of the thirteen 20 Kg batches and the 20 single trimmings were referenced for fat as described above (2.2)

3.6 Analysis of measurements including estimates of prediction accuracy for single trimmings and batches of varying size

This analysis has been based on all the weights and predicted fat values for all trimmings contained in the batches. Estimated fat content in the 3 big batches were compared with the microwave results. The 20 Kg batch results were compared with chemical measured fat content. The results for the 20 Kg batches were combined to make bigger batches in order to estimate levels of accuracy for different batch sizes.

The newly scanned single trimmings were joined with the earlier 25 single trimmings. Estimated prediction of accuracy could thus be made for single trimmings, and the data was also used to estimate fat content and prediction errors for larger batches of trimmings.

4 Results and Discussion

The following presents the results of the work discussing the findings of the project in each section.

4.1 Calibration

Fat content in the 26 calibration samples ranged from 2.1 to 82.7 % fat. The main calibration model is based on the average spectra from the 26 frame samples on day 1. The models presented in the report are all based on the SNV corrected spectra. When the models were developed different calibration strategies were evaluated, however, only the main results are reported here.
The prediction error estimate used to evaluate the models is root mean square error of prediction (RMSEP)

RMSEP = square root of [{ (predicted fat – measured fat)^2} / N], where N is the number of samples.

Roughly, one can count on that the accuracy of the calibration is ± 1 RMSEP.

4.1.1 Fresh samples

QVision AS had previously collected data from coarsely ground meat with another scanner in another plant. It was possible to include this data in the model if beneficial. A reason for including them is to base the model on a larger set of data, improving the basis for calibration. It turned out that the data sets could be combined after SNV correction, but not beforehand.

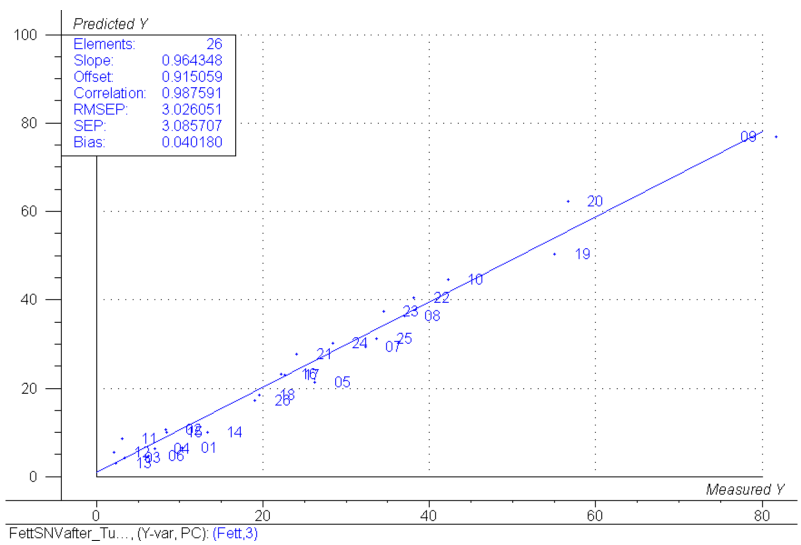


Figure 4.1 Cross validated fat model based on the 26 calibration frames.

Figure 4.1 shows the cross validated model based only on the crates measured at Nortura Tunga plant. The model is based on 3 PLSR components, and is suitable to use on new average spectra from new samples, or to be applied on every single pixel in scans to obtain images of the fat distribution. This holds for all the calibrations developed in this work. An accuracy of RMSEP=3.0 % is comparable with measurements on other meats such as pork. Combining the data from Nortura

Tunga plant with the old data produces a model which is slightly improved (Figure 4.2). RMSEP is reduced to 2.8%. This is the model that was implemented at Nortura Tunga plant for the second set of trials.

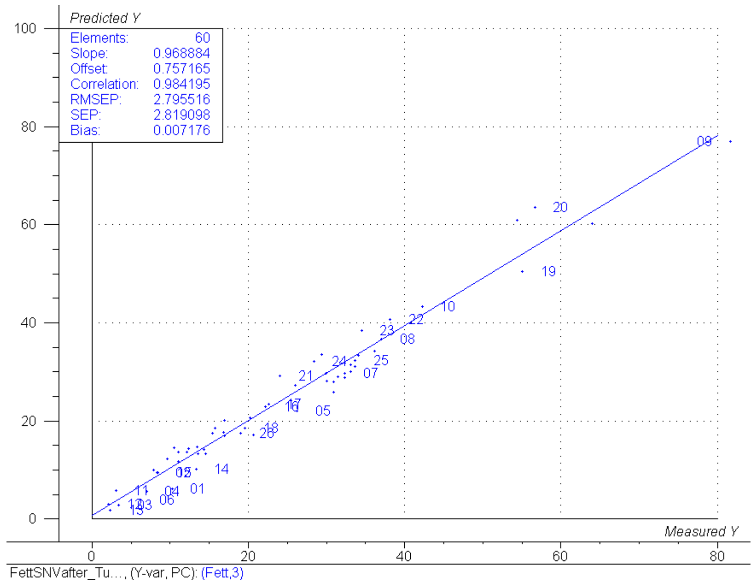


Figure 4.2 Fat model based on Tunga data and old beef data.

The data was tested on the meat from the crates placed on the conveyor belt. This is not a very conservative test, since it is the same meat, but it still gives a hint about the ability to measure on beef spread out on the conveyor. Figure 4.3 presents this works showing a correlation of 0.99 and RMSEP of 2.8%.

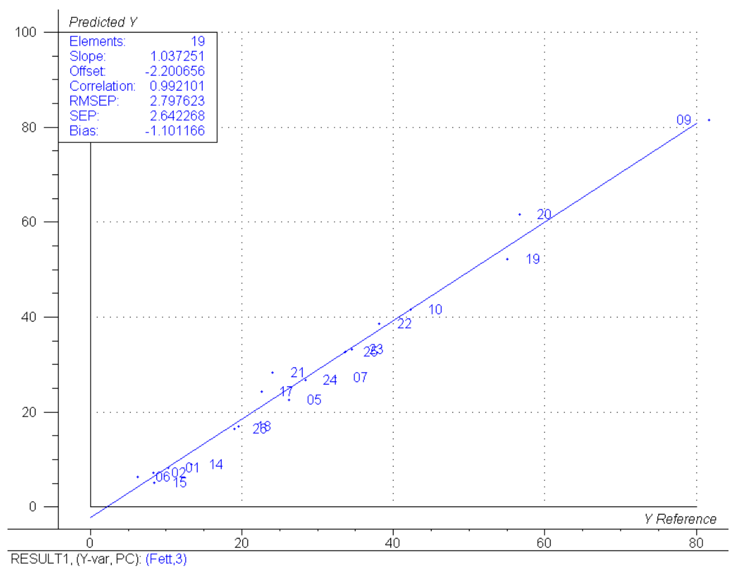


Figure 4.3 Model tested on the calibration samples, but with trimmings spread out on the conveyor belt. (Not all 26 calibration samples were scanned like this)

4.1.2 Frozen samples

When the meat is frozen, the NIR spectra change due to a temperature related shift that is induced in the water peak since the water molecules are bound in a different and more tight way (Figure 4.4). This effect can actually be used to estimate quantitatively the fraction of water which is frozen.

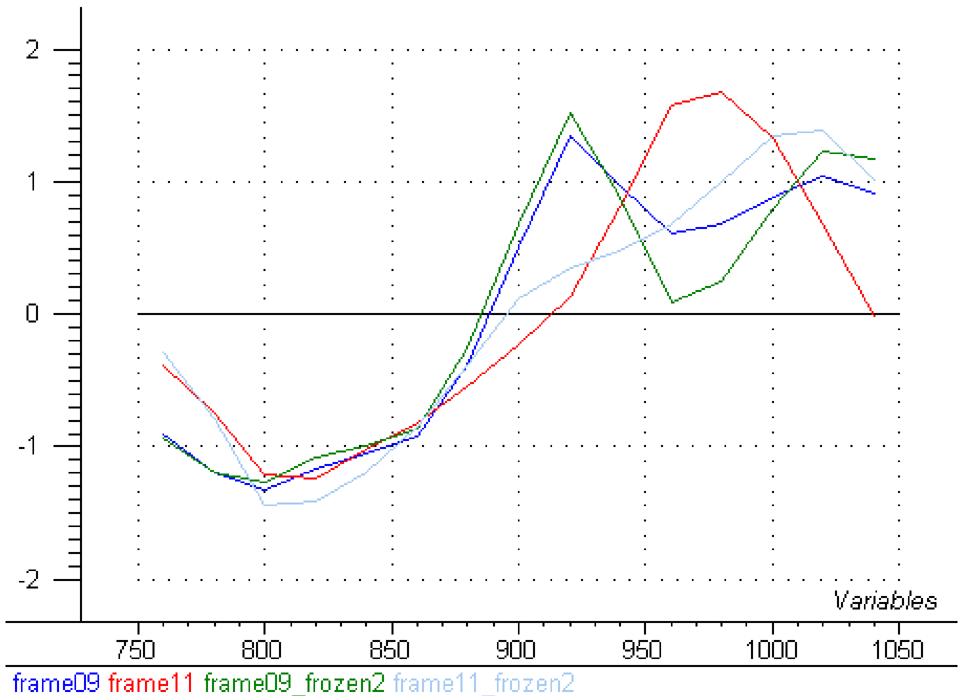


Figure 4.4 Frame 9 fresh (blue), frame 9 frozen(green), frame 11 fresh (red), frame 9 frozen (light blue). There is a prominent shift in the water peak towards higher wavelengths when the meat is frozen. The fat peak is fixed.

This shift is not a problem when modelling fat, but, if the temperature varies a lot between samples, calibration scans should be recorded for different temperatures and included in the model.

The samples used in this experiment were supposed to be deep frozen (-18℃), while after overnight freezing, some of th e samples were not colder than -3℃ in central parts of the block.

Modelling based on frozen samples worked well, and the cross-validated model is shown in Figure 11. A proper and independent test set for frozen samples was not available, but the model clearly indicates that it will be possible to measure fat in frozen blocks of beef also. The model is less accurate than the models for fresh beef. This can be due to varying temperature (not all samples were frozen solid), the smaller amount of the samples that were scanned, and possibly an effect of lower signals from the frozen material.

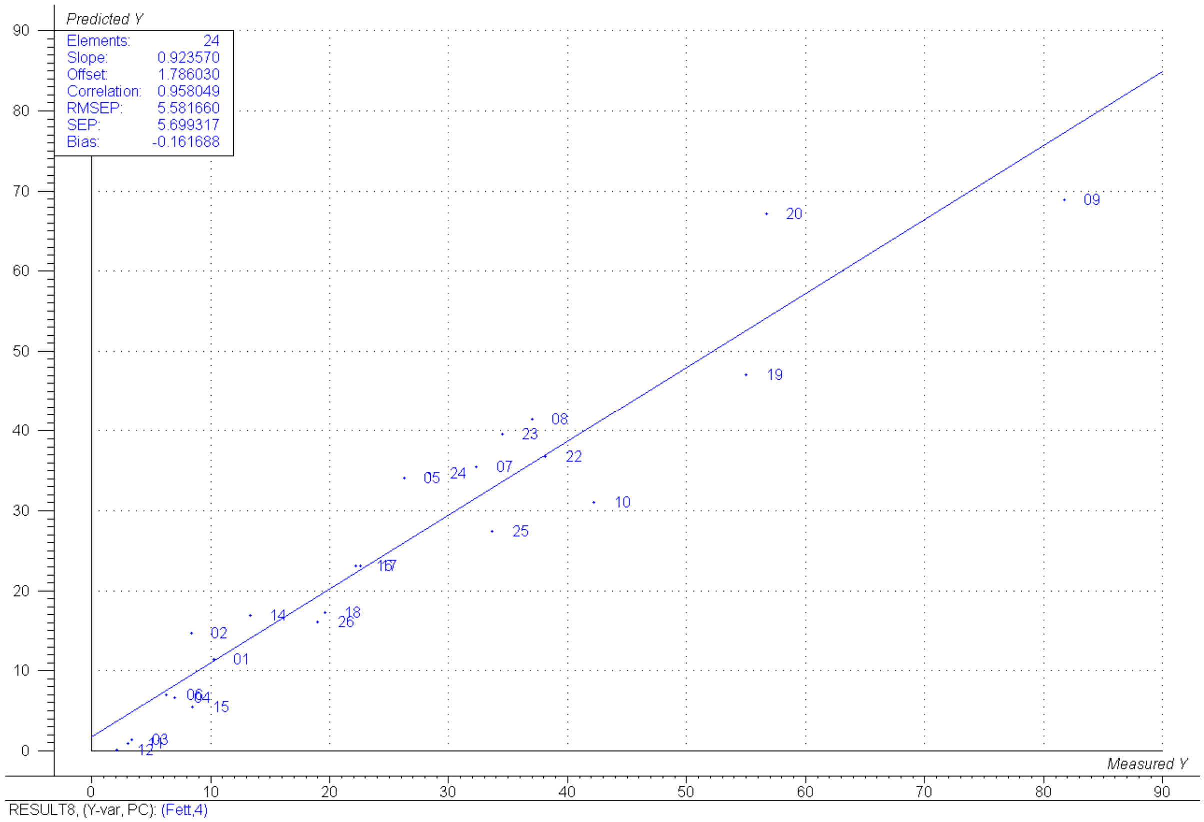


Figure 4.5 Fat calibration for frozen blocks of beef. 25 of the calibration samples were scanned as frozen, and one sample was removed from the model regarded as an outlier.

4.2 Validation of model on single trimmings and batches

This section presents the performance of the above model on fresh beef for different cases; single trimmings, large batches and smaller batches. Note that all the data is new (new meat recorded 3 weeks later than the initial calibration data), so the results represent a realistic test of the model and scanner concept.

4.2.1 Model validated on single trimmings

Included in this section is the study of single trimmings from trials at Nortura Tunga plant, a total of 45 trimmings. Each trimming were scanned 2-3 times at different sides (Figure 4.6). All the scans are included in the results to illustrate the effects of heterogeneity.

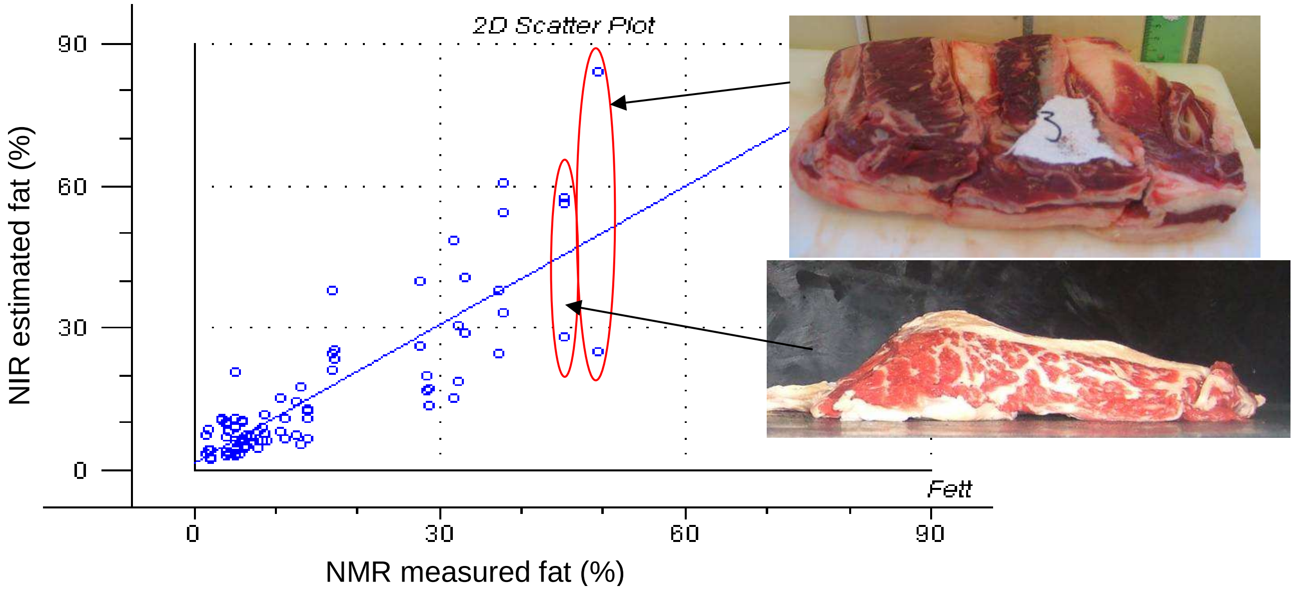


Figure 4.6 NIR predicted vs. NMR measured fat in single trimmings. Correlation is 0.84.

The accuracy of the predicted values does not look very impressive, but at the same time as expected; the higher the fat, the greater the prediction errors. The red ellipses enclose predictions from the same samples, and illustrate the great differences in fat estimates that can occur when a trimming is covered with fat on one side and is lean on the other. Leaner trimmings are more homogeneous, and more accurate estimates can be expected. An RMSEP value of 8.7% was obtained for these data.

Of the 45 samples, there were three samples that gave quite different spectra compared to the others. The signals were very low, and the shape of the spectra was slightly different; the water peak tends to be shifted towards lower wavelengths. The samples of question are very lean, but the spectral shift results in far too high fat predictions (Figure 4.7). It is suspected the samples to be Dark Firm Dry (DFD) meat, normally with a high pH, but the pH of these samples were normal. It might be the structure of the meat samples that gives the effect. Pictures of the samples are shown in Figure 4.6. Other trimmings with low fat content were well predicted.

It is important to clarify the causes of this effect and how to handle it. It can be mentioned, that if a regression model is based on the trimmings only (and not the calibration samples), then these three samples fit fairly well into the model, which means that this problem can probably be overcome.

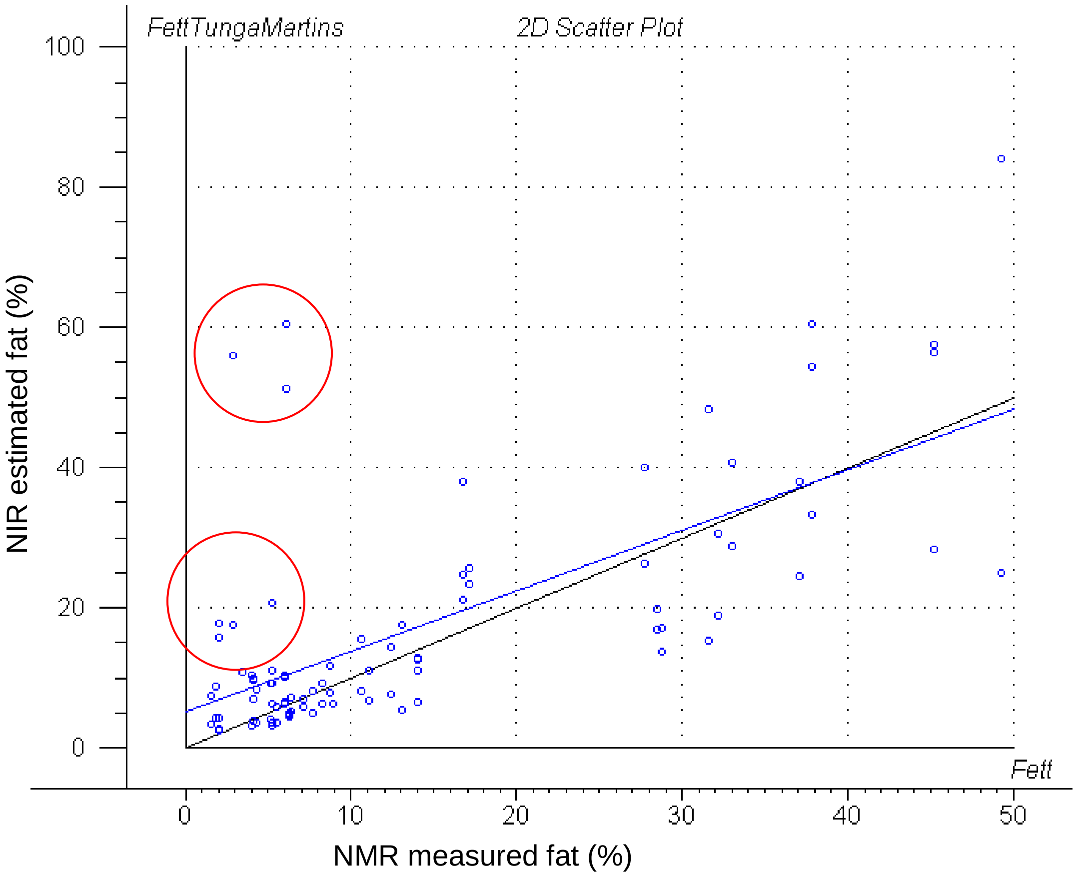


Figure 4.7 Predicted fat content in trimmings, including the outliers (circled)

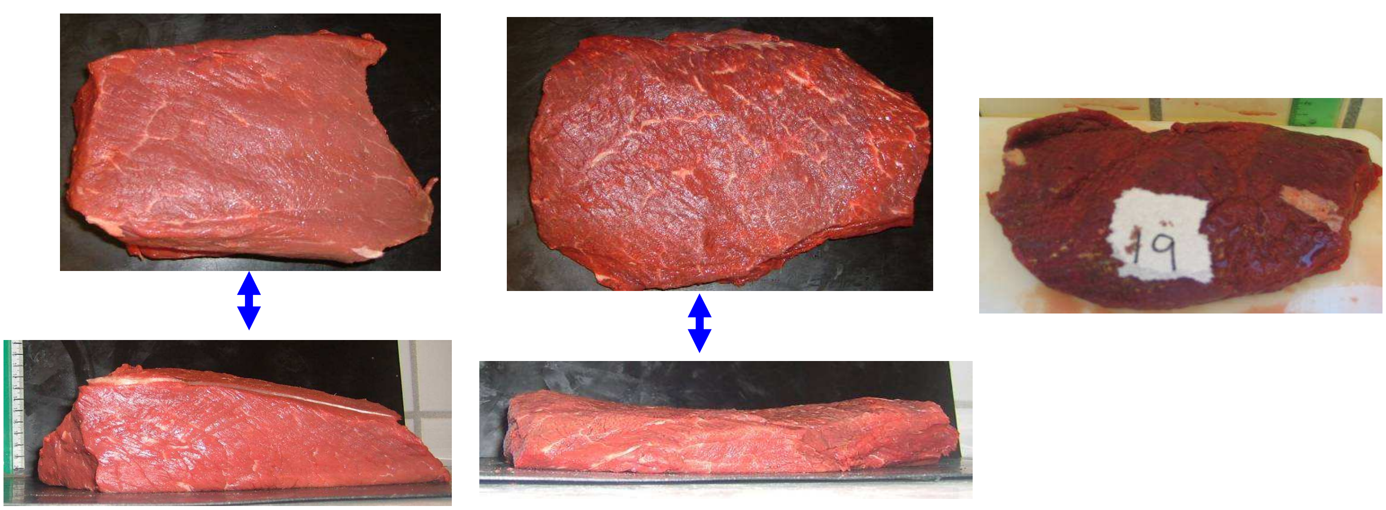


Figure 4.8 The 3 incorrectly classified lean samples. Flat and lean.

4.2.2 Accuracy as function of batch size (simulation with trimmings)

For each of the single trimmings the weight, NMR measured fat, and two or more NIR estimated fat contents are recorded. This information can be used to simulate the accuracy for bigger batches.

The simulations were done as follows:

RMSEP values for batches of size 5 to 100 Kg were estimated. For each batch size, 2000 different batch combinations were randomly put together. For each batch, the NIR estimated and NMR measured fat content were calculated. An RMSEP value was calculated based on the 2000 batches. To illustrate the differences for low fat beef and high fat beef, simulation were made of RMSEP for trimmings of fat <8% and >30% respectively and for the entire population. Figure 4.9 summarizes the simulation results. Lean meat generally gives lower prediction errors also for bigger batches, but the difference is reduced with increasing batch size. Already at batch size 5 Kg the RMSEP is reduced considerably compared to single trimmings (7.8%), and at 20 kg, a prediction error of about 1.5% is obtained (1% for lean meat, 1.5% for the whole population).

The simulations clearly indicate that the quite high prediction errors for single trimmings, are reduced to acceptable levels already at quite small batches (10 – 20 kg). This will also depend on the size and heterogeneity of the trimmings.

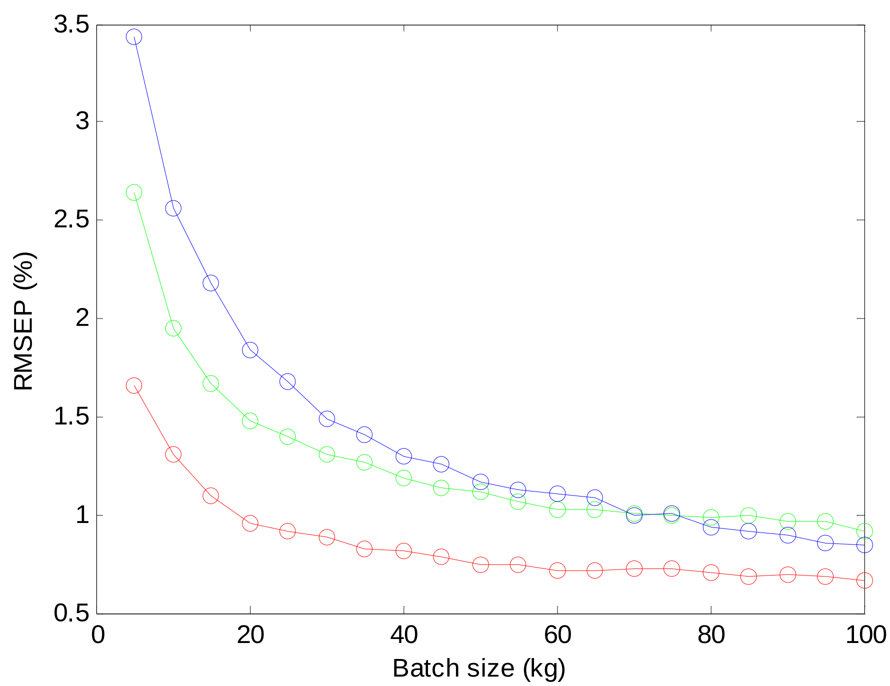


Figure 4.9 RMSEP as function of batch size based on simulations with single trimmings. Red: Simulation with lean trimmings (< 30% fat). Blue: Simulation with fat trimmings (> 8% fat). Green: Simulation with all trimmings.

4.3 Model validation on large batches

Three large batches of beef trimmings were scanned, and based on estimated fat content and weight of the different trimmings or portions of trimmings; the average fat content for the three batches was estimated

The three batches were taken directly from production. Table 1 summarizes the results.

	Qmonitor on beef trimmings	Inline microwave on ground beef	Batch Weight (Kg)
14-% quality:	6.9	7.5	164
14-% quality:	14.3	13.8	145
21-% quality:	10.9	11.3	170

Table 1 Average fat estimation in big batches of beef

There is not sufficient data to estimate any differences between the NIR system and the microwave system outputs but our impression is that they measured the same. In fact, the Inline microwave system was sensitive to the speed of the grinder in that if a fat part of the meat passed slowly by the sensor, it was weighted more heavily in the estimation of the batch average than if it passed quickly by the sensor.

With the scanner, this is avoided since fat estimate of every sample is also connected to measured weight of that sample, which of course is impossible for the ground meat passing the Inline system.

The figures in Figure 4.10 shows the on-line output from the scanner for the three batches, and how fat estimates in intact trimmings are accumulated and averaged to a rather stable weighted average value after about 20 Kg of accumulation.

The figures illustrate that the accumulated average stabilises after 20 – 30 Kg of measured beef, and the target fat content can then be controlled to a desired value by adding fat or lean meat. The amount of meat needed to get a stabilized average estimate depends mostly on the batch heterogeneity.

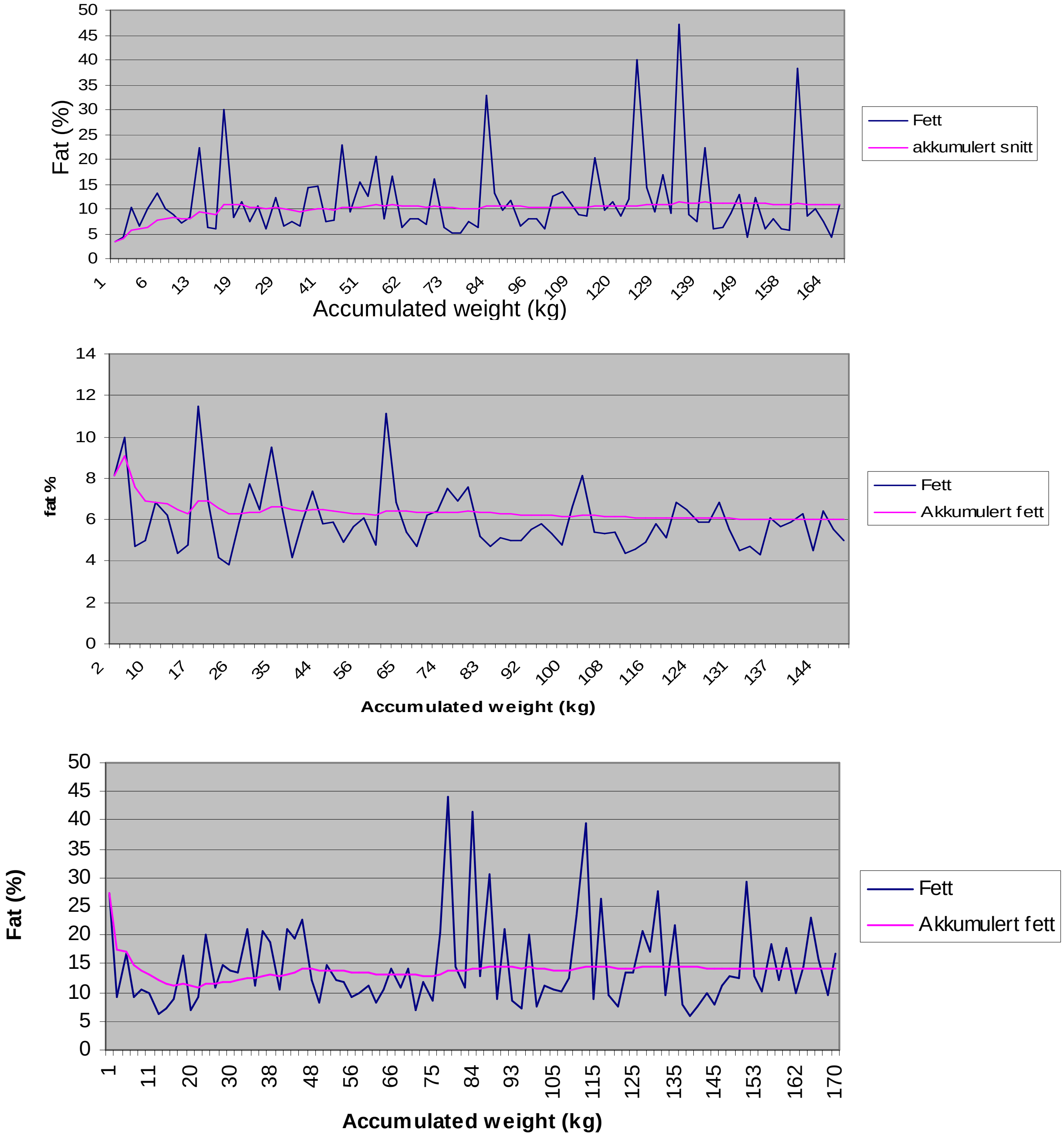


Figure 4.10 Single fat estimates and accumulated average fat values for the 3 batches

4.4 Model validation on smaller batches

This section relates to the 13 smaller batches weighted between 10 and 25 kg. Table 2 summarizes the results for these batches.

Batch no	Weight	Estimated fat % NIR scanner	Measured fat % NMR	Difference
1	22.74	9.56	8.20	-1.36
2	23.43	8.22	9.60	1.38
3	22.64	10.77	10.40	-0.37
4	24.68	9.44	8.60	-0.84
5	22.82	11.10	10.00	-1.10
6	22.17	9.41	9.80	0.39
7	19.13	10.23	10.70	0.47
8	10.11	10.40	10.20	-0.20
9	15.97	27.89	31.00	3.11
10	18.24	6.93	8.50	1.57
11	19.73	16.75	18.30	1.55
12	15.19	21.47	22.30	0.83
13	10.40	20.85	22.20	1.35

Table 2 on-line predicted and reference values for average fat % in small batches

The correlation is 0.99 and the RMSEP is 1.34%, significantly lower than obtained for the calibration models. The results correspond well with the simulations based on the single trimmings (Figure 4.11). The largest prediction error (3.1 % for batch 9) is for a high fat batch. This is not surprising, since these batches are often more heterogeneous and more meat is needed to obtain a stable result. Note also that the size of this batch was quite small.

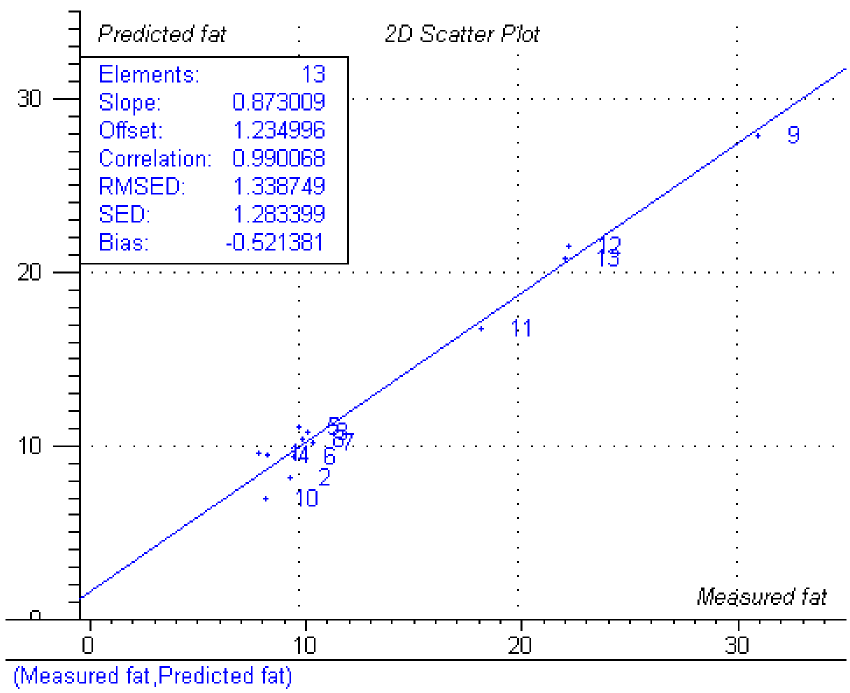


Figure 4.11 Predicted vs. measured fat % in small batches (around 20 kg) of beef.

4.4.1 Accuracy as function of batch size (simulation with batches)

Based on the results of the small batches, the NIR predicted and NMR measured fat contents for combinations of these batches can be evaluated. This can give us an impression of how the prediction error will vary with batch size. This was done by making all possible combinations of the batches, where 2, 3, 4, 5 and 6 boxes were combined.

The number of possible batch combinations increases with the number of batches to join. Combination of batches gives for

2 batches: 78
3 batches: 286
4 batches: 715
5 batches: 1287
6 batches: 1716 different combinations.

The same batch is never used twice in the same combination. The large amount of batches makes many of the combinations very similar, but not equal. The high number of combinations does not affect the estimation of RMSEP, except that it can be done quite accurate (Figure 4.12).

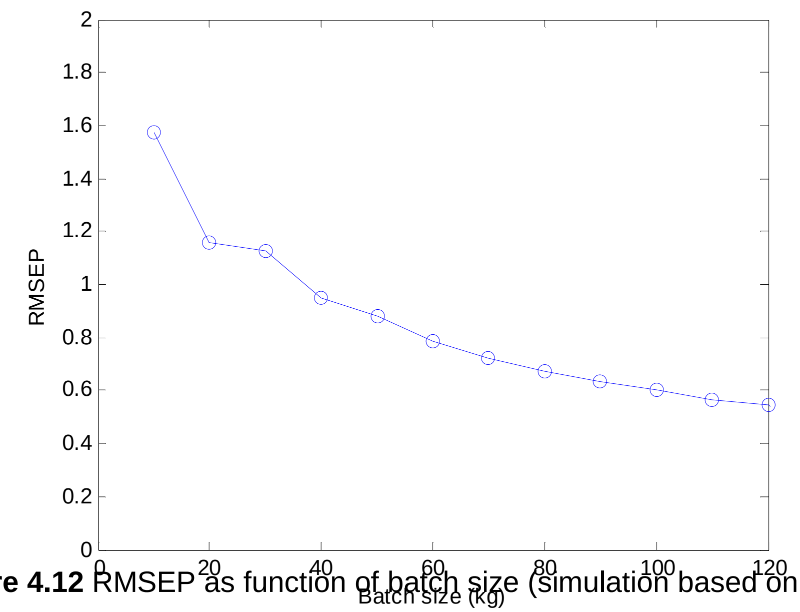


Figure 4.12 RMSEP as function of batch size (simulation based on 13 batches)

It can be see that the RMSEP again decreases with increasing batch size, and that the values from these calculations are comparable with those based on the single trimmings.

5 Success in Achieving Objectives

The project has successfully tested the NRI technology for trimmings of beef meat and the results provide the basis for the continuation of the work to reach a practical implementation of QVision in an Australian plant.

6 Impact on Meat and Livestock Industry

The impact of the results is considered high, especially in reducing the need for skilled labour in the grading and sorting of trimmings as well as general handling for the packing of trimmings to meet customer specification, both in target case weight and in CL. In the next 12-24 months and subject to further developments, NRI technology in the form of QVision equipment may be integrated to meet the needs of the larger processors at a price that is about half the equivalent x-ray technology, whilst providing the opportunity in labour saving as well as improvement in give away. In the next 2-4 years and subject to developments the technology improved to meet the requirements of the meat sector in Australia would have wide spread applications allowing savings in give away by about 1.5%-2% of volume of trimmings.

7 Conclusions and Recommendations

The main conclusions of the project are outlined below:

- Good calibration models were obtained for fat content in beef trimmings (R=0.98, RMSEP=2.8%). The developed model can be used on single pixels to get a picture of fat distribution, or it can be used on the average spectrum from each trimming/portion of trimmings. In this study, the last approach was used.
- An acceptable fat calibration was also obtained for frozen calibration samples, with a somewhat higher prediction error (R=0.96, RMSEP=5.6%). A significant variation of temperature was observed in the samples. Each sample was scanned twice as opposed to the fresh samples, which were scanned six times. The result is promising and it is likely that a reliable model for frozen blocks is possible.
- The fat model applied to 43 single trimmings, with average fat content ranging from 1.6-49.3% fat, resulted in a rather high RMSEP (8.7%) and a correlation of 0.84. This was expected as the heterogeneity of the trimmings affects the measurements; high prediction errors for fat/heterogeneous samples and lower for lean samples.
- Three samples gave spectra that did not fit into the calibration model. These were lean samples, while the fat estimates were very high. Optical signals were very weak from these samples, and spectral shape slightly different from the others. Yet, the reason for these deviations is not known. It is suspect that the structure of the meat might play a role here. This should be investigated further. It seems that the effect can be modelled satisfactory into a future calibration.
- Simulations based on fat estimates in single trimmings indicate that the prediction error decreases with batch size, and already for batches of 20 Kg the RMSEP is down at about 1.5%.
- Test measurements on true batches in the range of 10 – 24Kg verify this result with an obtained RMSEP of 1.33%.
- Simulations with the batches indicate again that the RMSEP decreases with increasing batch size and, for the present case, reaches about 0.6% for 100 Kg batches, which should be sufficient.
- A test with the QVision scanner on 3 big batches of 145, 164, and 170 Kg gave the same fat estimates as the Inline microwave system obtained on ground meat.
- In summary, it is proven that the NIR scanner can give reliable and accurate fat estimates of batches of beef trimmings, including smaller batches. The concept should be suitable for on-line

estimation of fat in trimmings in order to determine the batch fat content and also to control the formation of batches to different target fat levels. A requirement for the concept to work properly is that the trimmings or layer of trimmings on the belt is not too thick. In this study maximum thickness was about 8 cm. Thicker trimmings might be used, but careful hardware adjustments might then be required.

- By combining the VIS and NIR modules in the Qvision scanner, it is possible to detect visible CT on beef trimmings. Small regions of CT can be difficult to detect, due to low image resolution, but larger sheets and chunks are detectable. Thin sheets of CT on top of fatty tissue can be difficult. Our impression is that CT detection can be used to separate high quality lean meat from low quality, CT rich meat.

It is recommended that a follow up project is supported by the MLA to achieve the following:

- Improve the range of QVision to scan meat trimmings that have a bigger height than currently possible with greater penetration, potentially scanning from above and below.
- Implement a complete solution in a plant in Norway to reach detailed and extensive field data on performance and quantification of savings
- Proceed to implement a first installation in Australia (Teys or Rockdale) to prove the same capabilities with Australian beef and to the expectations of the Australian industry, quantifying the benefits and validating the returns.
- To establish a supply route for rolling out the technology and provide after sales support for the QVision technology

It is expected that a follow up project under an MLA matched funding scheme would require a budget of about AU$ 900k.

It is also recommended that a parallel study could aim to bench mark x-ray technology with NRI comparing cost and performance. This is potentially and activity that can be undertaken by Nortura requiring a budget of approximately AU$ 700k. The MLA-AMPC contribution of AU$ 250k would be provide a major incentive for the work to proceed in Norway with the results being available to the MLA and Australian industry on a cost shared basis.

8 Bibliography

Skjervold, P.O., Wold, J.P., Taylor, R.G., Berge, P., Abouelkaram, S., Culioli, J., Dufour, E. 2003. Development of intrinsic fluorescence multispectral imagery specific for fat, connective tissue and myofibers in meat. J Food Sci. 68 (4): 1161-1168