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EXECUTIVE SUMMARY

Background	Deliverable D7.3 detailed descriptors to be calculated from activity data and Deliverable D7.4 applied these descriptors to predict the health status of cows.
Objectives	In the present deliverable, we refine the calculation of activity descriptors and extend the use of descriptors to predict animal health, stress, and efficiency.
Methods	The relationship between the circadian rhythm of dairy cow activity is further explored by Machine Learning. The relationship between feed efficiency and measures of feeding behaviour (and other sensor-based behavioural variables) is addressed by statistical analyses (univariate regression and multiple stepwise regression).
Results & implications	Activity patterns can be used to *distinguish cow states. Nearly 100* % days with no event are classified as normal. The proportion of correct classification of oestrus, calving, diseases, mastitis, acidosis, lameness ranges between 63 and 88%. If the method was implemented on a farm, very few false alarms would be received by a farmer, alarms could be refined with indication of the most probable cow state. Feed efficiency can best be predicted from measures of feeding behaviour. When added to measures of eating time, sensor-based parameters related to activity do not significantly contribute to the prediction of feed efficiency. There was no consistency between countries (Spain vs. the Netherlands) in the type of model that was obtained when predicting feed efficiency from measures of eating time and sensor-based parameters related to activity. So at present no common formula can be proposed.

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1 Introduction

The previous deliverable (D7.4) was focused on the relationship between sensor-based behavioural variables and measures of dairy cow health. More specifically, we established the extent to which postpartum health of dairy cows can be predicted based on their behaviour (eating, ruminating, standing, lying) before calving, and we studied the relationship between drinking behaviour and mastitis. Finally, results were provided on the modification of the circadian rhythm of dairy cow activity when the animals were stressed or diseased, regardless of the disease.

In the present deliverable has two main objectives:

- The relationship between cow health / stress state and dairy cow activity will be further explored; in particular, now a distinction was made between different disorders and events.

- The relationship between feed efficiency and measures of feeding behaviour, and between a wider range of sensor-based behavioural variables and feed efficiency will be addressed

- If strong relationships are obtained, the algorithms proposed can be implemented in Precision Livestock Farming tools 1- to monitor closely animals and take operational decisions (daily management) or 2- to phenotype animals – i.e. to characterise their potential – with a view to help strategic decisions.

2 Results

2.1 Refinement of calculation of activity descriptors

There is evidence that animals that feel unsafe or uncomfortable change more often of activity. For instance, when turned from pasture to indoors conditions, animals need to get used to their new environment; they may fraction their activity in small bouts, changing often from one activity to another (Veissier et al 1989). Similarly, sheep suffering from acidosis often change their posture from lying to standing (Commun et al 2012) as if they don't feel comfortable in either of these postures. By contrast the changing of posture may be difficult is some settings, resulting in longer bouts, or an activity can be prevented resulting in longer bouts of another; e.g. in poorly designed cubicles cows have difficulties standing in the cubicles and have longer lying bouts (Veissier et al 2004).

We define a new indicator on the fragmentation of activity. It measures the extent to which the activity of an animal is distributed in small bouts of given activities.

The fractioning of the activity is calculated as the number of bouts of a given activity during the day or whatever the activity. For instance, using scan sampling with one scan every 10 min, the following activities can be recorded for a given animal: Lying, standing, walking, eating. In the example below, the number of bouts during the for 6 h of observations are: lying, 2; standing immobile, 1; walking, 2; Eating, 1. The total l number of activity bouts is 6.

Scan	Activity
1	Lying
2	Lying
3	Lying

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4	Lying
5	Walking
6	Walking
7	Eating
8	Eating
9	Eating
10	Eating
11	Eating
12	Eating
13	Eating
14	Eating
15	Eating
16	Eating
17	Eating
18	Eating
19	Eating
20	Eating
21	Walking
22	Standing immobile
23	Standing immobile
24	Standing immobile
25	Standing immobile
26	Lying
27	Lying
28	Lying
29	Lying
30	Lying
31	Lying
32	Lying
33	Lying
34	Lying
35	Lying
36	Lying

For such calculations, the activities considered should be not too detailed. For instance, if one distinguishes between lying with different head, leg or body positions there will be many small activities whereas during all these activities the animal is resting so the biological significance is the same.

There are also edge effects: in the example above, the number of lying bouts per 6 h of observation may be only 1 on average over consecutive 6 h time series, -and not 2 as calculated - because the activity "lying" may continue from one series to the next. To reduce this problem, it is recommended to calculate bouts on long time series, at least 1 day long.

2.2 Activity and health

Improvement of the FBAT method using fuzzy logic

We suspect that the behaviour of a cow starts to be modified 1-2 days before clinical signs are detected and is still modified for few days thereafter. The probability for showing sickness behaviour should therefore increase for some days before clinical signs are obvious then should decrease when animals recover. We applied fuzzy logic to label days according to their closeness with the day clinical signs are detected. We then applied the FBAT method (presented in D7.4) using such fuzzy labels. Briefly FBAT models the circadian activity according to a mere sinusoid (wavelength = 24 h). If the Euclidian distance between two successive models exceeds a given threshold then FBAT considers that the rhythm has changed. By using fuzzy labels, we reduced the proportion of false detection: in the large dataset on commercial farms (100000 cow*days) only 5% (instead of 20% with the initial FBAT method) of normal days were detected abnormal.

Distinction between disorders (monitoring)

With the FBAT method we can detect changes in activity rhythm related to diseases, stress, or reproductive events (calving, oestrus). But we are not able to distinguish between these events.

We tried to adjust the threshold of FBAT to specific events with a view to distinguish them. We failed to find satisfactory results with this approach.

We then considered a series of statistical and time series descriptors that we calculated on each each*day:

- Autocorrelations
- Mean
- Standard deviation
- Asymetry
- Kurtosis
- Sum
- Minimum & maximum
- Quadratic mean
- Quantiles (10,25,50,75,90%)
- Root Mean Square of successive difference (RMSSD)

At first we used 32 descriptors (Table 1). We used Machine Learning – here Random Forest – to classify cow*days according to these descriptors. A first Random Forest was performed on all descriptors but one (due to a correlation of 0.99 with another descriptor). A second Random Forest was performed on 21 descriptors, the 10 descriptors with a weight lower than 3% having been removed. With these 21 descriptors, we were able to satisfactorily discriminate control days from days corresponding to a specific cow state (calving, oestrus, mastitis, lameness, acidosis, other diseases, accidents, stress due to mixing or to disturbances) (Table 2). On average on all datasets used more than 95 % days with no event were classified as normal, which implies that very few false alarms would be received by a farmer if the method was implemented on a farm. The proportion of correct classification of 24 h time series when an oestrus, calving, diseases, mastitis, acidosis, lameness occurs range between few percentages to over 60%. Actually, the events that are not correctly classified are very often classified as normal days (Table 3). This has to do with the fact that for each event an episode of several days before and after the event is labelled as abnormal (usually 2 days before, the day the event is detected, and the day after). The behaviour of the animal is not necessarily modified during all these days. Actually, there was 91%–100%

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probability of successfully detecting at least one 24-h series around a disease, oestrus or calving. The detection often occurred 1–2 days before the day caretakers noticed the event.

For this work we used data previously used to develop the FBAT method (see D7.4) and a dataset from IRTA. The former were obtained with a Real Time Locating System and the latter with accelerometer, thus suggesting that the method is not bound to a given sensor.

Table 1. The 32 statistical features describing 24-h time series of cows' activity level (referred to 'activity' in the table) with their average weight over the five datasets in the two random forest (RF) classifications descriptors.

Definition	Name	Weight (%) RF 1	RF 2
Minimum activity among the 24 h	Minimum	1.71	-
Maximum activity among the 24 h	Maximum	5.92	7.71
Mean activity over the 24 h	Mean	3.38	4.40
Root Mean Square, i.e. the square root of the mean of squared activities across the 24 h	RMS	3.13	4.14
Standard deviation of the activity over the 24 h	STD	3.10	4.12
Mean of the standard deviation of the 6 non-overlapping 6 h windows composing the 24 h	MeanSTD6h	2.34	-
Standard deviation of the mean of the 6 non-overlapping 6 h windows composing the 24 h	STDMean6h	2.03	-
Standard deviation of the difference between the activity of any hour and the activity of the next hour	STDSD	-	-
Root mean square of successive differences, i.e. the differences between the activity at an hour and the activity at the next hour	RMSSD	3.40	4.49
Most common value among the 24 h	Mode	1.74	-
Quantiles 10 and 90%, calculated from the values which divide the hours into 10 equal groups from lower to higher activity. Q10, maximum values of the lower group; Q90, maximum value of the last but one higher group	Q10 Q90	3.12 4.48	4.33 5.88
Quantiles 25, 50 and 75%, calculated from the values which divide the hours into 4 equal groups from lower to higher activity. Q25, maximum values of the lower group; Q50, median; Q75, maximum value of the last but one higher group	Q25 Q50 Q75	3.52 3.71 4.04	4.65 4.86 5.36
Symmetry of the distribution of activity across the 24 h	Skewness	3.41	4.43
'Tailedness' of the distribution of activity across the 24 h	Kurtosis	3.55	4.57
	Autocorr1	3.16	4.17

Autocorrelation, i.e. the correlation between the activity at any Hour h and the activity at Hour h + d, where d represents a fixed interval (1 h, 2 h, … 11 h)	Autocorr2	3.16	4.33
	Autocorr3	3.20	4.25
	Autocorr4	3.21	4.36
	Autocorr5	3.12	4.23
	Autocorr6	2.95	-
	Autocorr7	2.89	-
	Autocorr8	2.87	-
	Autocorr9	2.79	-
	Autocorr10	2.84	-
	Autocorr11	2.82	-
Harmonics 1, 2, 3, 4 in a Fourier Transform	h1	3.57	4.87
	h2	3.64	4.97
	h3	3.69	5.01
	h4	3.51	4.87

Table 2. 1000-trees Random Forest algorithm precision for each event with the last 10 descriptors as classification attributes. Results presented are averaged over 5 iterations, with train sample being each time a random subset of 2/3 of the original dataset) and test sample being the remaining 1/3.

		Dataset				
Cow state		**1**	**2**	**3**	**4**	**5**
Control days	Headcount	26110	5863	7755	1582107	11650
	% detected	100.0%	94.4%	100.0%	99.9%	99.8%
Oestrus	Headcount	758	140	551	13294	421
	% detected	37.0%	14.9%	53.7%	2.4%	35.9%
Calving	Headcount	251	0	0	12812	0
	% detected	22.9%	-	-	38.0%	-
Lameness	Headcount	109	491	0	8340	349
	% detected	38.9%	18.9%	-	2.6%	39.4%
Mastitis	Headcount	161	90	0	2423	180
	% detected	31.5%	2.9%	-	3.1%	33.8%
Acidosis	Headcount	0	3156	0	0	2495
	% detected	-	32.7%	-	-	54.2%
LPS	Headcount	343	0	0	0	0
	% detected	22.6%	-	-	-	-
Accidents	Headcount	0	0	0	1236	0
	% detected	-	-	-	5.0%	-
Other disease	Headcount	242	276	0	4736	33
	% detected	36.4%	14.8%	-	4.6%	24.3%
Mixing	Headcount	973	0	0	0	150
	% detected	32.8%	-	-	-	19.1%
Disturbance	Headcount	1432	6195	0	273439	191

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	% detected	31.5%	63.6%	-	2.1%	15.3%

Table 3. Confusion matrix from one Dataset 1

Predicted class

True class	Control	Oestrus	Calving	Lameness	Mastitis	Other	Mixing	Disturbance	At least 1 series	Detected day before
Control	100	0	0	0	0	0	0	0		
Oestrus	61	37	0	0	0	0	0	1	100	63
Calving	24	0	23	0	0	0	44	9	100	97
Lameness	64	0	0	36	0	0	0	0	100	96
Mastitis	36	0	0	0	39	0	18	7	100	98
Other disease	48	0	0	0	0	36	16	0	100	95
Mixing	46	0	11	0	3	4	33	3	92	
Disturbance	55	1	2	0	1	0	2	31	11	

2.3 Feeding behaviour pattern

We question if the feeding behaviour of a cow has an impact on its feed efficiency. More specifically we question if the time spent taking food vs. chewing the food by a cow during meal impacts on its feed efficiency. We looked at ways to identify this behavioural pattern.

The BioControl troughs monitor feed bin weight with an 1 g resolution and a 2 s sampling rate. Each cow is detected in the bin using its RFID tag and the raw weighting signal of the visit is collected in a SQL data base synchronized on the universal time. On the 10th june 2019, in one pen of the INRAE experimental farm Herbipole barn, 390 visits were collected from 12 lactating cows (6 Holstein, 6 Montbeliarde) having free-access to 12 BioControl troughs (6 with hay, 6 with maize silage). At the same time, two cameras (Axis, MediaRecorder 4, Noldus), placed in front of the bin, recorded cow's behaviour. Trained observers labelled the videos (gold standard measurement of head down (the cow takes a bite) or head up (the cow chews the food)) using the The Observer software (Noldus). A signal-processing algorithm was developed to automatically (1) access the data base from BioControl, (2) process the raw signal of each visit and (3) compare the results to the gold standard (Figure 1 below).

The algorithm consists in (1) re-sampling, synchronising and filtering noise from high and from low frequencies to keep only signal variation due to cow having head down in the bin, (2) standardizing the weigh variation to make all visits comparable, (3) detecting all local maxima in the signal, (4) thresholding the filtered signal to obtained a binary signal directly comparable to the gold standard at each second which allows the calculation of the Jaccard similarity index. From both signals (processed

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and gold standard), the frequency head down (predicted from Biocontrol and observed from videos) and the duration head down (expressed as % of the visit duration) were also calculated.

The 390 visits (mean duration = 9min 15s, Min=20s, Max=54min) were processed according to 27 combinations of the different parameters (filter size, threshold level). The higher Jaccard index (0.57) was obtained with the following settings:

- Re-sampling every second
- Synchronisation: delay of 13 s between Biocontrol and video data
- High frequency filter : data obtained on sequences of 4 s are averaged
- Low frequency filter : The minimum obtained in a &5 s sequence is deduced from the raw data

Then within a meal, we consider that there is a significant increase in the weight of the trough when the weight increases by more than 3% of the maximum weight during the meal.

With such settings, the method overestimates by 20% both the frequency and the duration. The coefficient of correlation r^2 between observed and predicted (n=390) are low, for the frequency (0.28) and the duration (0.24). Nevertheless once averaged per animal, the r^2 was increased for the frequency (0.74, N=12) but stay low for duration (0.09, N=12).

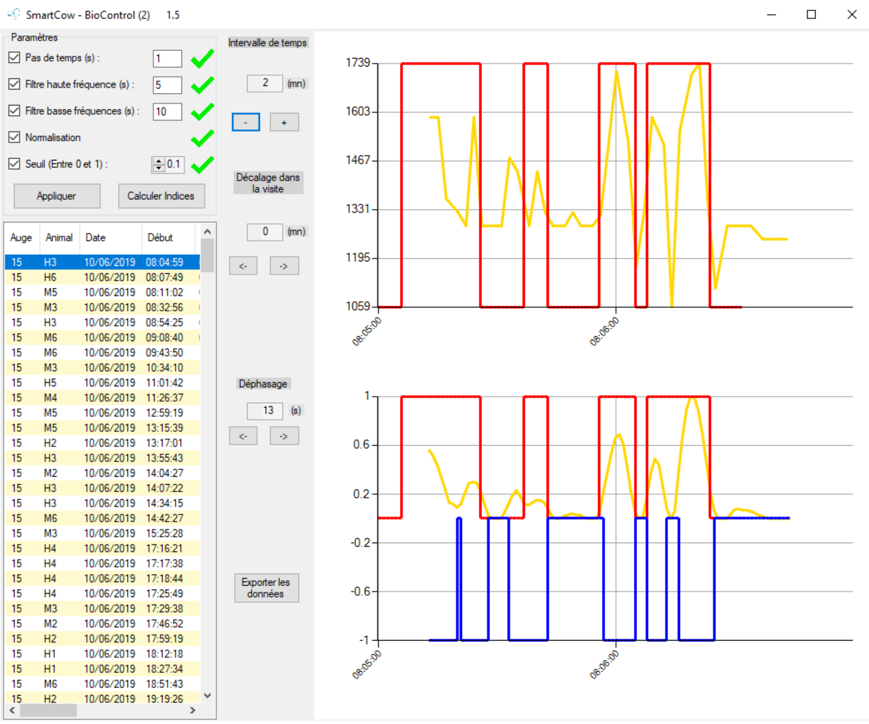

Figure 1. Output of the algorithm used to compare video observations and the variations in feed bin weight. Top left, setting of parameters. Bottom left, dataset. Top right, visualisation of raw data (yellow, feed bin weight; red, eating (1-yes/0-no) from video observation). Bottom right, visualisation of processed signal (yellow, feed bin weight; red, eating (1-yes/0-no) from video observation; blue, eating (-1-yes/0-no) from feed bin weight processed).

For the moment, we cannot reliably estimate the proportion of time spent eating vs. chewing during a meal from the variations of feed bin weights, such as with the BioControl system.

2.4 Feeding behaviour and feed efficiency

The relationship between measures of feeding behaviour and feed efficiency was examined using a data set obtained by IRTA.

An initial dataset of 40 Holstein dairy cows between 150 and 200 DIM from EVAM facility (Monells, Girona, Spain) was evaluated, and those cows with health events or incorrect feeding behaviour in the feed bins were discarded. Finally, a dataset of 30 dairy cows was used to study the correlations between feeding behaviour parameters and feed efficiency.

Data collected from those 30 animals were:

- Feed efficiency calculated as: energy-corrected milk (ECM, calculated as follows: *(0.3246 × kg milk) + (12.86 × kg fat) + (7.04 × kg protein)*) by TDMI (feeder + milking parlour)
- Average and variance of eating rate, number of meals, number of visits, eating time in the feeder, and meal size.

Data distribution, average, standard deviation and variance of eating behaviour parameters from the thirty cows are represented in the Figure 2 and 3 and Table4:

Table 4. Average, standard deviation, minimum and maximum value, and variance of performance and feeding behaviour parameters per cow.

Parameter	Average	Standard deviation	Minimum value	Maximum value	Variance
DIM	184	2.7	150	220	-
Lactation number	2.2	1.3	1	5	-
TDMI, kg/d	24.3	2.7	19.7	29.5	17.5
ECM[1], kg/d	30.5	5.21	18.3	41.2	11.6
Feed efficiency[2]	1.30	0.197	0.83	1.70	0.08
Feeding behaviour:					
Number visits/day	43	10.5	25.2	61.5	11.6
Time in the feeder, min	195	42.5	106	296	1579
Eating rate, g/min	262	55.8	178	407	2270
Number of meals/day	8.6	2.29	5.68	15.30	5.7
Meal duration	32	10.5	16.4	56.8	131

[1] Energy corrected-milk calculated as: (0.3246 × kg milk) + (12.86 × kg fat) + (7.04 × kg protein)

[2] Calculated as ECM/TDMI

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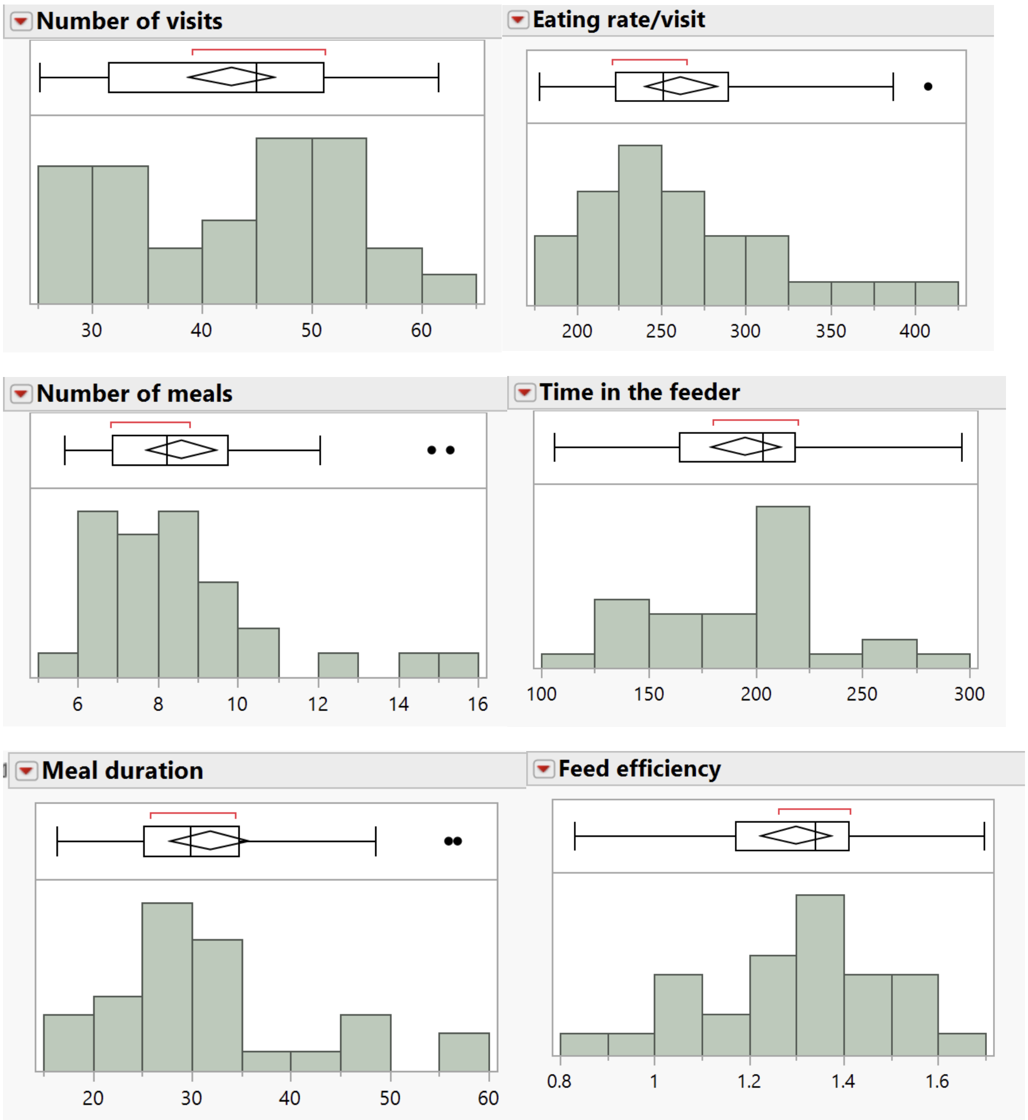

Figure 2. Distribution of the average of daily feeding behaviour parameters and feed efficiency per cow of the 30 dairy cows used in the dataset to establish relationships between feed efficiency and feeding behaviour.

Following data exploration, dispersion matrixes were done among eating behaviour variables to detect multicollinearity among them using the Pearson's correlation coefficient.

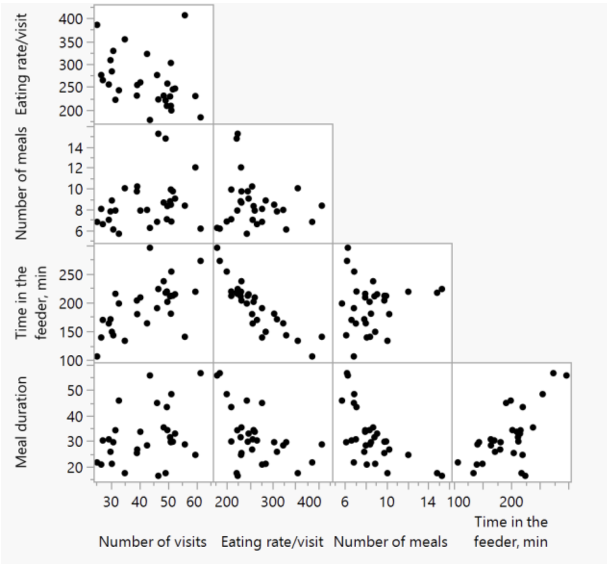

Figure 3. Dispersion matrixes between eating behaviour variables.

Time in the feeder was highly correlated with eating rate (Pearson's coefficient = -0.88), and moderately correlated with number of visits (Pearson's coefficient = 0.61), and meal duration (Pearson's coefficient = 0.65). Therefore, time in the feeder was discarded for the linear regression analysis.

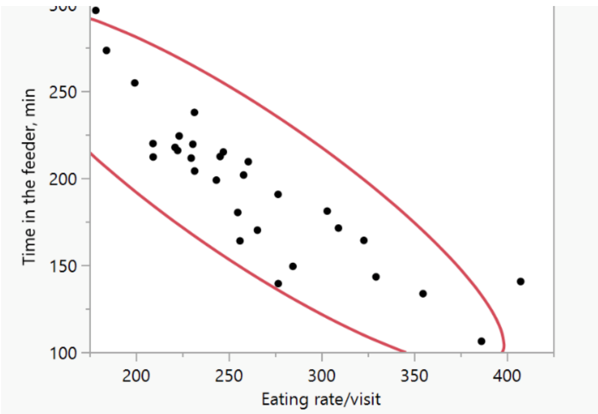

Figure 4. Correlation between eating rate and time in the feeder

To determine the extent to which the regression coefficients depend on the parity of the cow, an analysis of covariance was performed using the variable, the parity, and its interaction as fixed effects. Parity was significant for number of meals variable.

Then, eating behaviour variables described above with P < 0.20 in a univariate linear regression model to explain feed efficiency (Table 5) were kept for a final multiple regression approach. Results from the

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univariate linear regression models showed variables mean eating rate, mean of meal duration, variance number of visits and variance of meal duration with P < 0.20 (Table 5). Therefore, those variables were selected for a multiple forward stepwise regression analysis

Table 5. Main statistics from univariate linear regression models of eating behaviour variables and feed efficiency.

Variable	R-square	RMSE	P-value
Number of visits	0.04	0.196	0.29
Eating rate	0.15	0.185	0.04
Number of meals	0.002	0.200	0.81
Meal duration	0.08	0.193	0.14
Variance number of visits	0.12	0.188	0.06
Variance of eating behaviour	0.0003	0.200	0.93
Variance of number of meals	0.03	0.197	0.34
Variance of meal duration	0.09	0.191	0.10

The multiple stepwise regression analysis included eating rate and the variance of the number of visits in the model that better fitted feed efficiency. Finally, to fit the last model cow within parity was included as random effect before running the final model with the two covariates selected (R-adjusted = 0.27). In the final model, eating rate was negatively correlated with feed efficiency and the variance of the number of visits, positively. The final prediction equation was:

Feed efficiency = 1.53 + (-0.0014 × eating rate) + [0.0011 × var(number of visits)]

2.5 Sensor data for behaviour and feed efficiency

The relationship between sensor data for behaviour , including eating time and measures of activity, feed efficiency was examined using two data sets: Data set 1, obtained by IRTA, and Data set 2, obtained by WUR-DLO.

Data set 1

Feed efficiency data and sensor data for behaviour were available for 24 cows from the IRTA farm. The parity ranged from 1 to 4: 13 primiparous cows, 8 in second lactation, 2 in third lactation and 1 in fourth lactation. For each cow data were available for around 60 days DIM ranging from 48-114 to 258-318. Available data were feed efficiency data and sensor data.

Feed efficiency data: milk yield, ECM, body weight, DMI and FE. Data characteristics are provided in Table 6. The feed efficiency data were aggregated to cow level by taking the median value per cow.

Table 6. Characteristics for feed efficiency data per cow per day

	n	average	standard deviation	minimum	maximum
Milk yield (kg/d)	1400	33.18	7.17	12.34	57.07
energy-corrected milk (ECM) (kg/d)	1395	33.22	6.11	12.49	53.20
Dry matte intake (kg/d)	1202	22.52	5.46	7.76	40.10
Feed efficiency (ECM/DMI)	1198	1.57	0.47	0.47	3.26

Sensor data included the following behavioural measures: lying time, eating time and standing/walking time per hour (all in seconds, summing up per hour to 3600). Characteristics of the sensor data aggregated to day level are provided in Table 7.

Table 7. Characteristics for behavioural measures recorded with sensors, per cow per day

	n	average	standard deviation	minimum	maximum
lying time (h)	1469	12.6	2.3	3.8	20.5
eating time (h)	1469	2.6	1.0	0.0	4.9
standing/walking time (h)	1469	8.6	2.4	0.0	19.3

For each cow, each of these sensor-based behavioural measures was quantitatively transformed into the following five parameters (as described in Deliverable D7.3):

- average
- variance
- autocorrelation
- nonperiodicity
- FFT

This transformation, therefore, resulted a total of 15 sensor parameters met cow, i.e.: average lying time, average eating time, ..., FFT of standing/walking time. Pairwise correlations were examined between parameters, and of each pair of parameter pairs with a correlation of more than 0.6 one parameter was not included in the multivariate analysis to avoid multicollinearity.

The relation between feed efficiency data and sensor parameters was explored by three regression variants:

1. *Simple linear regression of feed efficiency data on sensor parameters*
   Sensor parameters for feed efficiency with p-value less than 0.2 are:
   - autocorrelation eating time
   - nonperiodicity milking time
   - FFT eating time
   - FFT milking time
2. *Multiple linear regression of feed efficiency data on sensor parameter and parity group*
   Sensor parameters for feed efficiency with p-value less than 0.2 are:
   For parity:
   - autocorrelation eating time
   - FFT eating time

   For the sensor parameters:

   - average milking time
   - variance eating time
   - variance lying time
   - autocorrelation eating time
   - nonperiodicity eating time

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- nonperiodicity milking time
- FFT eating time
- FFT milking time
- FFT lying time

3. *Multiple linear regression of feed efficiency data on sensor parameters and parity group with interaction.*

   Sensor parameters for feed efficiency with p-value less than 0.2 are:
   For parity:

   - average eating time
   - variance eating time
   - autocorrelation eating time

   For the sensor parameter:

   - average eating time
   - variance eating time
   - autocorrelation eating time
   - autocorrelation milking time
   - nonperiodicity milking time
   - nonperiodicity standing time
   - FFT eating time
   - FFT milking time
   - FFT lying time

   For the interaction:

   - average eating time
   - variance eating time
   - nonperiodicity standing time

For the multivariate model only parameters were included with p-value less than 0.2 in the multiple regression model with interactions. Parameters with p-values for the interaction term (covariate.Parity) less than 0.2 were excluded from the analysis.

The best subset selection model for the regression of feed efficiency on parity, autocorrelation eating time, nonperiodicity standing time, FFT eating time and FFT lying time resulted in a model based only on parity and FFT eating time:

FeedEfficiency = 2.216 – 0.129*ParityGroup – 0.468*FFT_EatingTime

A scatter plot for the observed versus the predicted values is given in Figure 5. The mean squared error is 0.0282, the adjusted R^2 is 0.344.

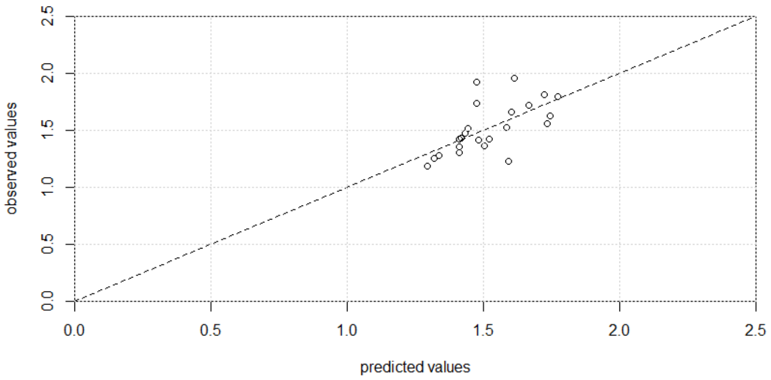

Figure 5. Observed versus predicted values of feed efficiency per cow calculated with a model based on parity group and the sensor parameter for FFT on eating time.

Data set 2

Feed efficiency data and sensor data for behaviour were available for 50 cows from the WLR farm Dairy Campus. The parity ranged from 1 to 7: 11 primiparous cows, 15 in second lactation, 7 in third lactation, 14 in fourth lactation, 2 in fifth lactation and 1 in seventh lactation. For each cow data were available for around 40 days in the start of the lactation, DIM ranging from 1-40 to 16-41. Available data were feed efficiency data and sensor data.

Feed efficiency data: milk yield, body weight, DMI and FE. Two cows with less than 14 days with efficiency data were excluded from the analysis. Data characteristics are included in Table 8. The feed efficiency data were aggregated to cow level by taking the median value per cow.

Table 8. Characteristics for feed efficiency data per cow per day

	n	average	standard deviation	minimum	maximum
Milk yield (kg/d)	1876	37.00	9.91	1.8	75.2
Dry matte intake (kg/d)	1648	18.01	4.32	1.92	27.99
Feed efficiency (Milk yield/DMI)	1609	2.17	0.70	0.28	8.29

Behavioural measures recorded with the neck sensor were: inactive time, active time, ruminating time, eating time and activity. Behavioural measures recorded with the leg sensor were: number of steps, number of bouts, lying time, standing time, walking time and standing/walking time per hour (all in minutes, summing up per hour to 60 min.). Characteristics of these sensor-based behavioural measures aggregated at day level are provided in Table 9.

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Table 9. Characteristics for sensor-based behavioural measures, expressed per cow per day

	n	average	standard deviation	minimum	maximum
inactive time (min)	1977	41.3	54.3	0	628
active time (min)	1977	674.3	149.8	277	1432
ruminating time (min)	1977	517.5	110.1	0	780
eating time (min)	1977	206.5	81.8	0	444
activity	1941	205.9	101.8	8	890
number of steps	1921	4378	1600	5	19331
number of bouts	1921	11.2	5.2	0	136
lying time (min)	1921	599.7	148.4	95	1440
standing time (min)	1921	788.5	140.8	0	1293
walking time (min)	1921	51.4	23.2	0	258
standing/walking time	1921	839.9	148.5	0	1345

For each cow, each of these sensor-based behavioural measures was quantitatively transformed into the following five parameters:

- average
- variance
- autocorrelation
- nonperiodicity
- FFT

This transformation resulted in a total of 55 parameters per cow: average inactive time, average active time, ..., FFT of standing/walking time. Pairwise correlations were examined between parameters, and of each pair of parameter pairs with a correlation of more than 0.6 one parameter was not included in the multivariate analysis to avoid multicollinearity.

The relation between feed efficiency data and sensor parameters was explored by three regression variants:

1. *Simple linear regression of feed efficiency data on sensor parameters*
   Sensor parameters for feed efficiency with p-value less than 0.2 are:
   a. AvgNeckmAct, VarNeckmRumi, AC_NeckmEat, AC_LegnStep, AC_LegmWalk, MSENeckmInact, MSENeckmRumi, MSENeckmEat, MSELegnUp, FFTNeckmEat, FFTLegnStep, FFTLegmWalk
2. *Multiple linear regression of feed efficiency data on sensor parameters and parity group*
   Sensor parameters for feed efficiency with p-value less than 0.2 are:
   For parity group 2:
   a. none parameters

   For parity group 3:

   b. all 55 parameters

   For the sensor parameters:

   c. AvgNeckmAct, AvgLegnStep, AvgLegnUp, AvgLegmWalk, VarNeckmInact, VarNeckmAct, VarLegnUp, VarLegmLie, VarLegmSsta, VarLegmStand, AC_NeckmEat, MSENeckmInact, MSENeckmRumi, MSENeckmEat, MSELegnUp, FFTNeckmEat, FFTLegnStep, FFTLegmWalk

3. *Multiple linear regression of feed efficiency data on sensor parameter and parity group with interaction*
   Sensor parameters for feed efficiency with p-value less than 0.2 are:
   For parity group 2:
   a. MSENeckmEat, FFTNeckmInact, FFTLegnStep,FFTLegmLie, FFTLegmWalk

   For parity group 3:

   - AvgNeckmEat, AvgLegmSsta, AvgLegmStand, VarNeckmEat, VarLegnUp, AC_NeckmInact, AC_NeckmAct, AC_NeckmRumi, AC_NeckAct, AC_LegnStep, AC_LegmLie, AC_LegmSsta, AC_LegmWalk, AC_LegmStand, MSENeckmInact, MSENeckmRumi, MSENeckmEat, FFTNeckmInact, FFTNeckmAct, FFTNeckmRumi, FFTNeckmEat, FFTNeckAct, FFTLegnUp, FFTLegmLie, FFTLegmSsta, FFTLegmStand

   For the sensor parameter:

   b. AvgLegmLie, AvgLegmSsta, AvgLegmStand, AC_NeckmEat, MSENeckmAct, MSENeckmEat, MSELegnUp, FFTNeckmInact, FFTNeckmRumi, FFTLegnStep, FFTLegmLie, FFTLegmWalk

   For the interaction 1:

   c. VarLegnUp, AC_NeckmEat, MSENeckmEat, MSELegnUp, FFTNeckmInact, FFTLegnStep, FFTLegmLie, FFTLegmWalk

   For the interaction 2:

   d. AvgLegmLie, AvgLegmSsta, AvgLegmStand, AC_LegnStep, AC_LegmWalk, MSENeckmInact, MSENeckmAct, MSENeckmRumi, MSENeckmEat, FFTNeckmInact, FFTNeckmAct, FFTNeckmRumi, FFTNeckmEat, FFTNeckAct, FFTLegnUp, FFTLegmLie, FFTLegmWalk

For the multivariate model only parameters were included with p-value less than 0.2 in the multiple regression model with interactions. Parameters with p-values for the interaction term (covariate.Parity) less than 0.2 were excluded from the analysis. Seven parameters remained for the all possible subset selection: AvgNeckmEat, VarNeckmEat, AC_NeckmAct, AC_NeckmRumi, AC_LegmLie, AC_LegmSsta, FFTLegmSsta.

The best subset selection model for feed efficiency (milk yield/DMI) was based on parity group, average eating time and variance of eating time:

Feed Efficiency = 1.953 + 0.224*ParGroup3 + 0.0378*AvgNeckmEat – 0.00234*VarNeckmEat

A scatter plot for the observed versus the predicted values is given in Figure 6. The mean squared error is 0.0682, the adjusted R^2 is 0.140.

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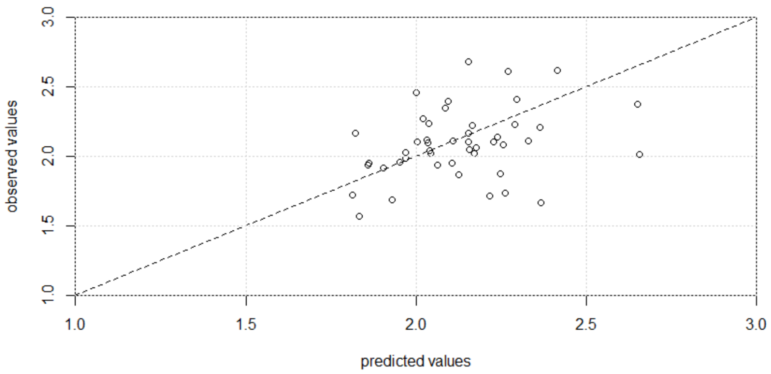

Figure 6. Observed versus predicted values of feed efficiency per cow calculated with a model based on parity group, the sensor parameter for average eating time and the sensor parameter for variance of eating time.

3 Conclusion

- It seems feasible to distinguish several internal states of animals (diseases, calving, estrus, stress) from their activity pattern (see paragraph 2.2)
- Feed efficiency can best be predicted from measures of feeding behaviour (see paragraph 2.4).
- When added to measures of eating time, sensor-based parameters related to activity do not significantly contribute to the prediction of feed efficiency (see paragraph 2.5).
- There was no consistency between countries (Spain vs. the Netherlands) in the type of model that was obtained when predicting feed efficiency from measures of eating time and sensor-based parameters related to activity (see paragraph 2.5).

4 References

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