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A correlated-variables model for monitoring individual growing-finishing pig's behavior by RFID registrations

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ABSTRACT

Feeding and drinking behavior of individual growing-finishing pigs can be used for health and welfare monitoring by real time warning systems. The objective of this study was to develop and test a model detecting deviating feeding and drinking behavior of individual growing-finishing pigs based on Radio-Frequency Identification (RFID) registrations. Feeding and drinking behavior of growing-finishing pigs was recorded through low frequency RFID readings via ear tags. In three 16-week batches, twelve pens containing each twelve pigs were equipped with one drinker and two feeders. Four readers (each with eight antennas) recorded feeding and drinking activity of each individual pig in the pens. All tag readings were combined into visits, and subsequently visits into meals. The analyzed variables were number of meals per day, average interval between meals and maximum interval between meals per day for both feeding and drinking. A correlated-variables model with a Kalman filter was developed, generating alerts when the daily level was deviating from the expected level. For illustration of model results, the model was validated with culling recordings, which included all pigs that died or were euthanized during the experiment. Most cases of culled pigs corresponded with alerts given by the model, but sensitivity was hard to determine due to low number of cases and specific circumstances of the culled pigs. The specificity of the model was similar for feeding and drinking behavior, and was highest for number of meals (93–99%), followed by the average interval between meals (90–96%) and the maximum interval between meals (86–97%), depending on desired confidence interval. The developed model is promising for early detection of health problems in growing-finishing pigs, but further validation should occur on a bigger scale in order to increase accuracy of results and improve knowledge required for practical implication of the model.

1. Introduction

In growing-finishing pig farming, increasing farm size and productivity lead to difficulties in monitoring of pig's health and welfare by farmers [1,2]. Farmers' daily checks through visual observation may be inaccurate and are known to cause changes in animal behavior due to human presence [3]. Automated monitoring of FDB was suggested to be valuable in early detection of health and welfare problems in cows [4–6] and pigs [5,7]. Feeding and drinking behavior are closely related [8], and are both important indicators for health and welfare of animals [9–11].

Feeding and drinking behavior of growing-finishing pigs can be quantified and examined in several ways. Next to the amount of feed or water consumed, the duration, frequency and rate of consumption are important variables in FDB [12]. Also non-nutritive visits, where no feed is consumed during visits to a feeding area, are important variables, as they can be used to monitor interest in the feeding area [13,14]. Hence, the complexity and differences in individual FDB requires individual monitoring of FDB of pigs in order to improve detection of health and welfare issues. This can contribute to preventing outbreaks of disease, decreasing usage of antibiotics, and allowing for a sustainable and economically efficient pig production.

The use of Radio Frequency Identification (RFID) registration has been previously reported to be suitable for monitoring of individual pigs [15–17]. Already two decades ago, single-space computerized feeding stations were used to record individual feed intake in group-housed pigs, mainly under experimental circumstances due to high costs of the feeding stations [18]. Nowadays, electronic RFID registrations can be used for monitoring of individual feed intake [19,20], and it is more cost-efficient than a computerized feeding station [21]. During a

Abbreviations: FDB, Feeding and drinking behavior.

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pneumonia outbreak, daily feeding time measured through RFID decreased in growing-finisher pigs treated for pneumonia [19]. Maselyne et al. [20] developed a detection model based on feeding patterns where severe health problems in individual pigs were detected on average within 1.3 days from the start of the health problem. Hence, monitoring of FDB through RFID registration may contribute to improving early detection and treatment of health and welfare issues in growing-finishing pigs.

Previous research into RFID monitoring mainly focused on either monitoring feeding behavior or drinking behavior. Monitoring both feeding behavior and drinking behavior can be useful in generating a more detailed behavioral pattern, thereby increasing accuracy in detecting potential health problems. Also, the development of early warning systems through the use of deviating behavioral patterns requires improvement before practical application [13,20]. Hence, the objective of this experiment was to study whether a correlated-variables model using a Kalman filter can be used to detect deviations in individual FDB in growing-finishing pigs based on low frequency (LF) RFID registration in order to improve detection of health problems. To achieve this, the first task was to develop a correlated-variables model using a Kalman filter detecting deviating FDB on individual growing-finishing pig level based on low frequency (LF) RFID registration. A second task was to evaluate the monitoring model, where illustrative results were generated.

2. Materials and methods

The experiments were conducted at the former Dutch Swine Innovation center (VIC Sterksel) in the Netherlands between June 2019 until November 2020. In the experiment, 12 pens were used with a size of 2.5 m width and 5.0 m long. Each pen was equipped with one drinker and two (combined) feeders (Fig. 1). The pens had a slatted floor. During three batches (Batch 1, Batch 2 and Batch 3) 12 growing-finishing pigs per pen were included in the experiment throughout their entire growing-finishing phase. The growing phase started around nine weeks of age and ended at slaughter which was around six months of age. Per batch, pigs were delivered to the slaughterhouse in one or two runs, depending on whether pigs had received the desired slaughter weight. This resulted in a growing-finishing phase ranging from 16 to 18 weeks. Weight data and slaughter dates per batch are presented in Table 1. Each pig was equipped with an LF RFID tag in the right ear.

Four readers, each with eight antennas were available to register the tag readings at each drinker and feeder (Agrident GmbH, reader type ASR650). Indoor climate data (temperature, relative humidity, CO_2 and NH_3) were continuously recorded in the room of the pens using one sensor (Hotraco Agri, Thomas® Climate). Daily visual health checks of all pigs were carried out by the caretaker aimed to detect health implications like lameness, lung problems and other diseases. Based on the daily health checks, decisions for treatment were taken. Data of treatments were recorded for Batch 2. Data of cullings (pigs that died or were euthanized during the experiment) were recorded for all three batches and used for validation of the monitoring results.

Table 1
Average start weight and end weight, and slaughter dates per batch of 144 pigs.

Batch	Average start weight (kg) ± STD	Average end weight (kg) ± STD	Slaughter date first delivery	Slaughter date second delivery
1	21.13 ± 4.27	114.29 ± 14.54	September 17th, 2019	October 10th, 2019
2	23.87 ± 3.54[2]	123.02 ± 11.93	June 16th, 2020	July 1st, 2020
3	23.26 ± 3.22	126.08 ± 14.73	October 21st, 2020	n/a[1]

[1] n/a = not applicable.
[2] n = 78.

In the second and third batch, one weighing platform (Hotraco Agri, Thomas® Animal Weighing system) was installed and created a passage at the back of two neighboring pens (see Fig. 1), resulting in a different pen design compared with Batch 1. For these two pens, weighing recordings were available anonymously and were not connected to a specific pig. Weighing recordings could therefore not used any further in this study, but this explains the difference in pen design in these pens.

For all three batches, readings of the RFID tags were recorded up to 10 times per second (ms). All reading data were saved per reader in separate files per day. For every reading, RFID number, date, time and antenna number was recorded. The combination of reader and antenna number identified a drinker or feeder. Microsoft Access was used for storage and preprocessing of the data. Tag readings were combined into visits based on a bout criterion of 20 s [16], meaning that tag readings with an interval of ≤20 s of the same pig and same location were combined into visits (s). The time stamp of the first reading was used as starting time, and the time stamp with the last consecutive interval that was ≤20 s as the ending time. In a following procedure, visits were combined into meals by applying a meal criterion of 900 s, which was calculated based on the method of Tolkamp and Kyriazakis [22]. Similar

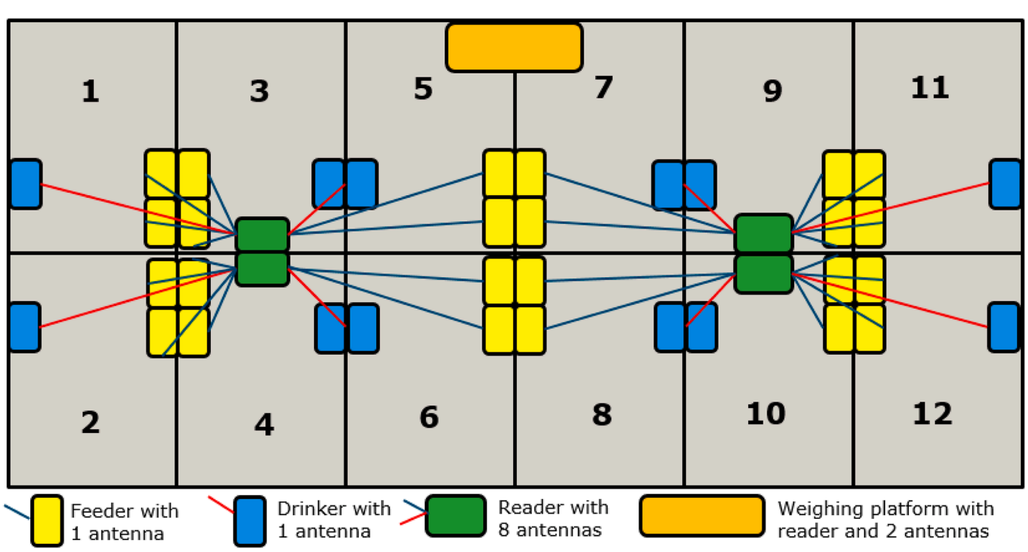

Fig. 1. (Color-printed): Overview of the experimental set-up of 12 pens, with each one drinker; two feeders; four readers, each with eight antennas; one weighing platform (with reader and two antennas) connecting pen 5 and 7 (only in Batch 2 and 3). Location of the readers and antennas are illustrative.

meal criterions for pigs are summarized by Maselyne et al. [11]. This resulted in availability of two types of behavioral variables: drinking and feeding.

The visits and meals per pig per day were used to develop the following characteristics for monitoring of individual pigs: number of visits per day, average interval between visits per day, maximum interval between visits per day, number of meals per day, average interval between meals per day and maximum interval between meals per day. For each of the six monitoring characteristics a similar correlated-variables model was developed. MATLAB [23] was used for further data processing. To determine correlated variables, Pearson correlations per pig of Batch 2 were calculated between all six monitoring characteristics and the following seven influence variables: the value of the characteristic yesterday, the value on the day before yesterday, the average value of all pig in the same pen on the same day, the average temperature on the same day, the average CO_2 concentration on the same day and the average NH_3 concentrations on same day. Variables with high number of pigs with significant ($P < 0.05$) correlations for all six monitoring characteristics were selected for the model. The same selection procedure of correlated variables was used for all six characteristics.

A linear relationship of the characteristic and the selected variables was assumed. A Kalman filter was used to fit the parameter values in this relationship per pig daily. An observation equation and a system equation are needed for a Kalman filter [24]. The following observation equation is applied:

$$Y_t = F'_t\theta_t + v_t,\ v_t \sim N[0, V_t], \tag{1}$$

In these equations Y_t is an observation vector, θ_t is the state vector, F_t is the design matrix which describes the relation between the state and the observation, v_t is the random observation error and V_t is the variance.

The system equation was:

$$\theta_t = G_t\theta_{t-1} + w_t,\ w_t \sim N[0, W_t], \tag{2}$$

Where G_t is the system matrix, describing the relation between current state t and the previous state t-1. The system matrix was independent of pig and day; w_t is the system error and W_t is the variance.

The final model was ran for each pig and every day for each monitoring characteristic. A correctly detected case was defined as a case of which an alert was generated within the last seven days with recording data before a culling event. The sensitivity of the model was determined following Eq. (3) indicating the percentage of correctly detected cases per batch. Specificity was determined following Eq. (4) indicating the percentage of healthy days without alert per batch.

$$\text{Sensitivity } (\%)^{1} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{Specificity } (\%)^{1} = \frac{TN}{TN + FP} \tag{4}$$

1) TP = True Positive, number of cases with one or more alerts given by the model that overlaps with a culling recording over a seven-days period preceding the culling date, FP = False Positive, the number of days with alerts given by the model that do not show an overlap with a seven-days period preceding culling dates, FN = False Negative, the number of cases without any alert in a seven-days period preceding the culling date, TN = True Negative, the number of days without an alert outside a seven-days period preceding culling dates.

An overview of the number of tag readings and percentage of days with uptime less than 20 h per batch is shown in Table 2. Per visit, an average of 131 tag readings were used. Per meal an average of 5 visits was used. Per batch around 160 million tag readings were recorded. Due to technical problems (mainly network problems as a result of broken wires), in Batch 1 51% of the reading hours were missing (uptime less than 20 h per day), in Batch 2 28% was missing and in Batch 3 30% was missing. If no readings were available during one hour, this hour was classified as a failure hour. Also the first hour with readings before and after the failure hour were classified as a failure hour, as it was uncertain when readings started again. Days including a failure period were not used for analysis, and intervals between visits on one day were not determined if the period before the visit/meal overlapped with a failure period. An illustration of the number of meals at the feeder and drinker during the 16-week cycle of one pen of Batch 2 is shown in Fig. 2. Gaps indicate missing data. The pigs of Batch 2 are delivered to the slaughterhouse in two runs, which explains the sudden drop in number of meals from day 171 onwards.

For illustration of the available data, all recorded visits to the drinker and feeder in a pen on one day are presented in Fig. 3. Visits can be to a drinker or one of the two feeders (feeder visits are combined). In general, periods with activity from all pigs in the pen alternate with resting periods where activity is low.

3. Results

A correlated-variables model was developed predicting the daily level of meals to a feeder and drinker per pig. The analysis of potentially correlated variables is presented in Table 3. From this analysis, the following correlated variables for feeding and drinking were determined: the value of the day before the day of interest, the value of two days before the day of interest and the average value of the other animals in the same pen on the day of interest. Little correlations between

Table 2
Percentage of days with uptime less than 20 h, number of readings, visits and meals for feeding and drinking per reader (reader 5 is on the weighing platform) per batch.[1]

Batch	Item	Reader Nr. 1	2	3	4	5	Total
1	days uptime < 20 h	36%	61%	68%	62%	n/a[2]	51%
	# readings	48,729,315	38,373,559	31,247,852	33,024,646	n/a	151,375,372
	# visits	299,279	245,988	196,077	198,649	n/a	939,993
	# meals	58,820	50,835	42,990	44,350	n/a	196,995
2	days uptime < 20 h	49%	26%	23%	30%	11%	28%
	# readings	31,675,394	46,228,483	43,866,491	44,780,502	1660,406	168,211,276
	# visits	227,302	349,709	327,865	331,887	43,166	1279,929
	# meals	39,688	71,770	68,736	63,989	22,262	266,445
3	days uptime < 20 h	30%	30%	38%	25%	38%	30%
	# readings	38,399,708	44,993,180	38,446,086	52,029,279	868,299	174,736,552
	# visits	301,600	350,340	257,558	358,507	21,724	1,289,729
	# meals	53,580	67,448	53,481	69,850	13,791	258,150

[1] In Batch 2 and 3 reading interval of the antennas was lower than in Batch 1 to reduce the amount of readings.
[2] n/a = not applicable.

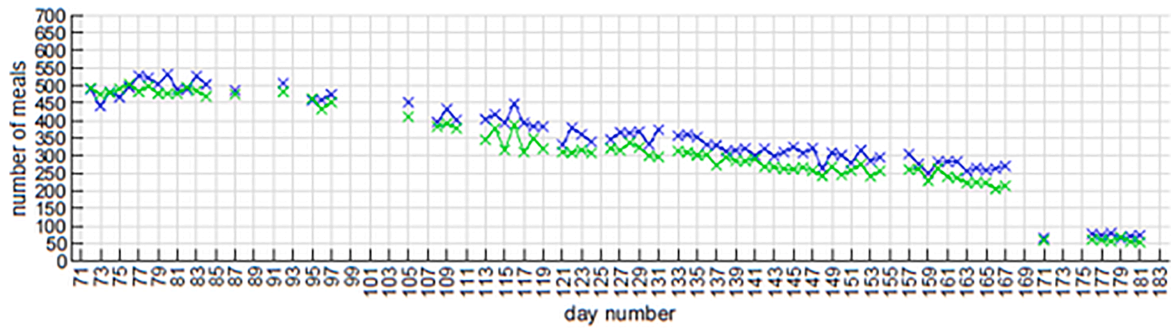

Fig. 2. (Color-printed): Daily number of meals at the feeder (green) and drinker (blue) during the 16-week growing-finishing cycle of one tag reader in Batch 2.

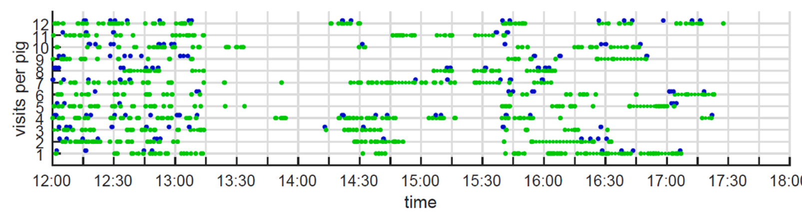

Fig. 3. (Color-printed): All visits of 12 pigs in Pen 2 of Batch 2 between 12:00 and 18:00 hr on March 11th, 2020; each line represents all drinking visits (blue) and combined feeding visits (green) of one pig.

Table 3
Number of pigs in Batch 2 with significant Pearson correlations (P-value < 0.05) for number of meals, maximum meal interval and average meal interval, per meal type and influence variable out of a maximum of 144 pigs.

Variable	Type	Value yesterday	Value day before yesterday	T (°C)[1,2]	RH (%)[1,3]	CO_2 conc.[1]	NH_3 conc.[1]	Value over all pigs in the same pen[1]
Number of meals	Drinking	126	106	11	45	43	37	140
	Feeding	127	111	7	43	43	46	142
Average interval between meals	Drinking	43	38	7	15	13	19	102
	Feeding	72	67	6	28	20	24	125
Maximum interval between meals	Drinking	83	86	15	42	36	29	136
	Feeding	104	95	14	40	35	42	139

1 Average value.
2 T = temperature.
3 RH = relative humidity.

FDB and climate were found, and this data is therefore not used in the model.

Eq. (3) shows the model equation for number of meals as an example, which was constructed based on the correlated variables.

$$\mathrm{NrMeals(d)} = \alpha_1 + \alpha_2 \cdot \mathrm{NrMeals(d-1)} + \alpha_3 \cdot \mathrm{NrMeals(d-2)} + \alpha_4 \cdot \mathrm{AvgNrMeals(d)} \quad (3)$$

where d = today, d − 1 = value of yesterday, d − 2 = value of the day before yesterday, α_1, α_2, α_3 and α_4 = parameter for the respective variable.

For the other feeding and drinking variables (average interval between meals and maximum interval between meals) the same equation applied. The values of the parameters α_1, α_2, α_3 and α_4 appeared to vary between pigs and appear to be time dependent. Therefore, a Kalman filter was used to fit these parameter values per pig on-line [25]. The following observation matrix is used in the Kalman model:

$$F_t = [F_{11}\ F_{12}\ F_{13}\ F_{14}]$$

Where $F_{11} = 1$, F_{12} = the value on the day d-1, F_{13} = the value on day d-2 and F_{14} = the average value of all pig in the same pen on day d. The system matrix was equal to the identity matrix. In this way, values were updated per pig per day, together with a variance-covariance matrix for these values that can be used to calculate confidence intervals (CI). Age effect is not corrected for, as the Kalman filter takes the development and the corresponding change in behavior of the pig into account by using the historical data of each pig individually. Alerts were generated when the difference between predicted and real level for a pig on a day is too big. If pigs had either a deviating (when error is outside CI) for one or more of the feeding or drinking variables (e.g. number of meals, average interval between meals and maximum interval between meals) an alert was generated. Several CI options were considered: a 95%, 99% or 99.9%. An example of the monitoring process of meals to the drinker and feeder for one pig is depicted in Fig. 4.

The first illustrative results of the model include classification results (Table 4) and results on specificity and false positive alerts (Table 5). For both feeding and drinking, number of meals per pig per day is the most suitable variable to use in generating alerts when the level is deviating from the expected level. Classification results differed per batch and variable (Table 4). Sensitivity ranged from 0 to 100%, but is not presented further due to unreliable results due to limited number of culling cases and effects of specific circumstances per case. For Batch 1, the high level of technical problems resulted in low detection of deviating FDB. In three out of the four cases, an increased maximum interval between meals was detected for both feeding and drinking. In Batch 2, a decreased number of meals, increased average interval between meals,

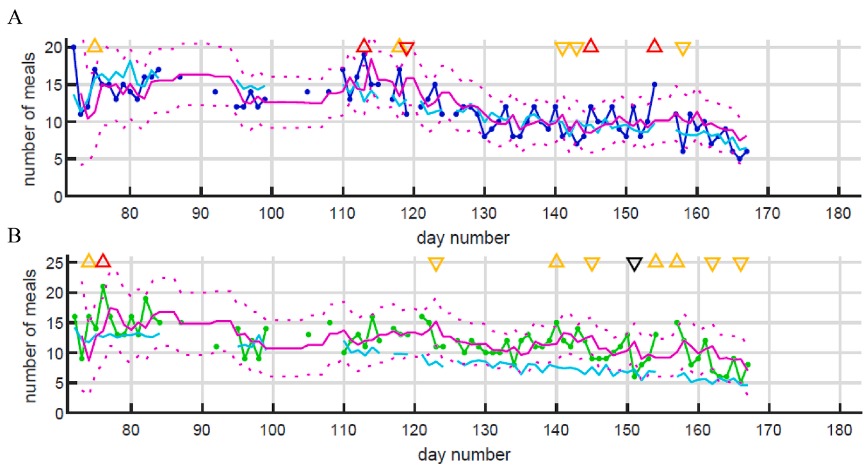

Fig. 4. (Color-printed): Example of monitoring per pig with numbers of meals per day to the drinker (A, blue dots connected by solid line) and feeder (B, green dots connected by solid lines) relative to January 1st, 2020. For both plots: solid cyan is average number for this pen, solid magenta line is fitted value (with dotted magenta line as 95% confidence interval (CI)) and alerts in top line when value is outside the CI (▽ for decreased values, Δ for increased; orange for 95%, red for 99% and black for 99.9% CI).

Table 4
Classification results of Batch 1 containing 4 cases (A), Batch 2 containing 5 cases (B), Batch 3 containing 5 cases (C) based on number of meals per day, average interval between meals and maximum interval between meals for feeding and drinking for all cases of culled pigs.[1,2]

A			Case Nr.				
Batch 1	Variable	Type	1[3,5]	2[3]	3[3]	4	
	Decreased number of meals	Drinking	–	–	–	–	
		Feeding	–	–	–	–	
	Increased average interval between meals	Drinking	–	–	–	–	
		Feeding	**	*	–	–	
	Increased maximum interval between meals	Drinking	–	–	**	***	
		Feeding	–	–	**	***	
	Missing days per case		6	5	7	2	
B			**Case Nr.**				
Batch 2	Variable	Type	1[4]	2[5]	3[3]	4[3]	5[3]
	Decreased number of meals	Drinking	*	–	*	***	–
		Feeding	**	***	*	*	–
	Increased average interval between meals	Drinking	***	***	**	*	–
		Feeding	–	–	–	–	–
	Increased maximum interval between meals	Drinking	***	*	**	***	–
		Feeding	–	–	***	–	***
	Missing days per case		0	7	6	6	4
C			**Case Nr.**				
Batch 3	Variable	Type	1	2[5]	3[5]	4[3,5]	5[4]
	Decreased number of meals	Drinking	**	***	**	**	*
		Feeding	*	–	–	*	***
	Increased average interval between meals	Drinking	***	***	***	***	***
		Feeding	***	***	***	***	*
	Increased maximum interval between meals	Drinking	***	***	***	–	***
		Feeding	***	***	**	–	***
	Missing days per case		1	1	1	7	–

1 *=outside 95%, **=outside 99%, ***=outside 99.9% confidence interval.
2 Sensitivity results have not been calculated due to limited number of cases.
3 Missing data during seven days before the case date.
4 Case in first days of the experiment (only 3 days available).
5 Alerts generated before case period.

and increased maximum interval between meals was detected for drinking in four out of the five cases. For feeding, number of meals decreased for all five cases. One case was culled in the first days of the experiment, resulting in little reliable data to predict FDB of this animal.

In Batch 3, decreased number of meals and increased average interval between meals was detected for both drinking and feeding in all five cases. An increased maximum interval between meals was detected for both drinking and feeding in four out of five cases. In every cycle, technical problems resulted in missing data in the days before some of the culling cases.

For all batches, specificity was highest for number of meals (93–99%), followed by the average interval between meals (90–97%) and the maximum interval between meals (86–97%), depending on desired confidence interval (Table 4). Number of valid days was lower in Batch 1 compared with the other two batches. This can be attributed to a high percentage of missing records due to technical errors in this batch (Table 2).

4. Discussion

The objective of this study was to develop a monitoring model detecting deviating FDB on individual pig level based on LF RFID registration in order to improve detection of health problems. The first illustrative validation results of the developed model are promising, but further validation is required. Sensitivity of the model could not be determined as only a few cases of culled pigs were available per batch and some of these cases had little data recordings available due specific circumstances. To calculate specificity sufficient data was available. Both for feeding and drinking, specificity was higher for number of meals (93–99%) than for the average (90–96%) and maximum (86–97%) interval between meals, depending on desired CI. For a reliable model adequate specificity is required in order to reduce the number of false alerts, and adequate sensitivity is required to detect the as many health problems as possible. In a similar study by Maselyne et al. [20], a model using the concept of Synergistic Control for numbers of feeding visits showed a sensitivity of 58.0%, and a specificity of 98.7%. Another study developing a warning system to detect water intake variation in sows reported specificities ranging from 32% to 92% and sensitivities ranging from 34 to 83% [26]. For practical application one should balance between desired sensitivity and acceptable specificity, and further validation of the current model should take place on a bigger scale in order to gain sufficient cases of health problems.

A high performance of the warning system is desired, but hard to achieve due to the complexity of FDB. For example, deviating behavior does not necessarily have to be associated with health problems, but may be attributed to other influences like change in diet, climate, defining the social ranking or other stress factors. Also, some animals may show a gradual, long-term change in behavioral pattern which may not be detected by the model but can be associated with subclinical disease. In a previous study of De Mol et al. [27], day-to-day variation of cows behavior was used to detect lameness problems. In this study a

Table 5
The number of valid days, the number of false positive (FP) alerts and the specificity (%) per confidence interval (90%, 99% or 99.9%) of Batch 1 (A), Batch 2 (B) and Batch 3 (C) based on number of meals per day, average interval between meals and maximum interval between meals for feeding and drinking for all pig days outside culling periods.

A				FP alerts			Specificity (%)		
Batch	Variable	Type	Valid days	95	99	99.9	95	99	99.9
1	Decreased number of meals	Drinking	5886	597	193	51	93.8	97.8	99.3
		Feeding	5809	544	180	53	95.1	98.5	99.6
	Increased average interval between meals	Drinking	5852	968	636	385	92.5	95.0	96.8
		Feeding	5786	959	634	385	92.1	95.1	97.3
	Increased maximum interval between meals	Drinking	5852	1146	636	350	86.7	91.5	94.9
		Feeding	5786	1179	703	381	86.5	91.7	95.3
B				**FP alerts**			**Specificity (%)**		
Batch	Variable	Type	Valid days	95	99	99.9	95	99	99.9
2	Decreased number of meals	Drinking	9380	496	172	36	94.6	98.4	99.6
		Feeding	9115	465	129	33	95.4	98.8	99.7
	Increased average interval between meals	Drinking	9293	899	596	376	90.9	93.9	96.1
		Feeding	9040	969	631	388	90.2	93.8	96.2
	Increased maximum interval between meals	Drinking	9293	1082	595	325	89.7	94.3	97.1
		Feeding	9040	1101	639	356	90.6	94.5	97.0
C				**FP alerts**			**Specificity (%)**		
Batch	Variable	Type	Valid days	95	99	99.9	95	99	99.9
3	Decreased number of meals	Drinking	9919	363	129	42	94.0	98.1	99.5
		Feeding	9667	287	88	22	94.4	98.1	99.5
	Increased average interval between meals	Drinking	9894	439	290	188	90.2	93.6	96.1
		Feeding	9655	458	284	156	90.1	93.4	96.0
	Increased maximum interval between meals	Drinking	9894	779	496	297	88.4	93.6	96.5
		Feeding	9655	784	480	273	87.8	92.7	96.1

quadratic-trend model was fitted with a dynamic linear model on-line per cow which allowed detection of gradual development of lameness over time [27]. Development of a similar model could be valuable in the current study, in order to improve the detection of gradual behavioral changes. Also, it may occur that a certain health problem is not accompanied with a change in the measured FDB variable in this model at all. Hence, the alerts generated by the model are useful for easy practical application, but farmers should always be cautious and not fully rely on the system.

The first illustrative results of the model are promising. The model was tested based on Batch 2 and validated using all three batches. For Batch 2 culling and treatment recordings were used to compare the alerts given by the model with the health status of the specific pig. Only including culling recordings and excluding treatment recordings only resulted in a minor change in results, due to low number of treatment recordings and high correlation between treatment and culling recordings in individual pigs. Therefore, it was decided to only use culling recordings for validation of all batches, also because the treatment data of Batch 1 and 3 is missing. With this validation method however, health treatments and undetected problems not leading to a culling remain unvalidated. This may also be partly attributed to the defined case period of seven days before a culling. In some cases significant changes in behavior were detected days or weeks before the defined case period, and these were therefore indicated as false positive alerts. This deviating behavior may however already be an early indication of a health problem. Inclusion of treatments recordings, and detailed analysis of false positive cases, including video analysis, could contribute to reducing false positive alerts and thereby increasing the model performance. Also, elaboration of the model with other monitoring variables like daily weighing recordings, combined with a daily health check by a trained researcher or veterinarian could contribute to a more detailed and accurate monitoring system. Overall, further model validation is required based on more validation data to improve the accuracy of the system.

Two pens in Batch 2 and 3 contained a weighing platform, equipped with readers. These readings were not used in the study because of absence of suitable visit criteria and meal criteria in literature. During sickness, animals generally decrease their time spending eating and drinking, and increase their resting time [6]. Hence, differences in individual visiting patterns to the weighing platform compared with visits to the drinker and feeders can give more detail in individual behavioral patterns, thereby allowing more accurate detection of deviations. To achieve this first suitable visits criteria and meal criteria should be developed.

When clustering the tag readings into visits, no minimum of readings was required to be turned into a visit. Generally, tag readings take place several times per second. However, some visits only consist of one tag reading. In a similar study of Maselyne et al. [17] this issue was tackled through including a minimum visit duration criteria of 5 s. Visits that were shorter than 5 s were excluded from the analysis, thereby increasing model sensitivity but decreasing precision of the model. It can be questioned whether it is fair to include these readings as a visit in the current model. For further validation of the system, the relevance of a minimum of tag readings required for a visit should be considered and the appropriate minimum level should be investigated.

Technical problems in the data collection mainly arose from networking problems as a result of broken wires and unstable internet connection. Generally, this resulted in missing data for several consecutive hours or days. To be able to construct a reliable behavior pattern of the pigs, missing data for more consecutive days increases the risk of missing a deviating behavior. Hence, to reduce the occurrence of technical problems, suitable systems for pig stables with robust wires or wireless data transfer should be further developed and implemented to increase reliability of the system.

The use of RFID ear tags for individual monitoring is not common in commercial growing-finishing pig farms. The lifespan of pig production is relatively short, making individual identification relatively expensive compared with group monitoring [28]. Nevertheless, individual identification was shown to be more specific compared with group averages [15–17,29], thereby potentially reducing long-term on-farm health costs [30,31]. Also, RFID technology can be used in farm management systems [32], and antibiotics-free certification in pig production. Hence, an integrated warning system using RFID registrations should be developed also including the pre-weaning and weaning period of pigs to decrease costs for monitoring, or in combination with other farm registration or monitoring systems. This contributes to improved disease detection over the entire pig's lifespan, thereby increasing sustainable pig production.

5. Conclusion

The correlated-variables model developed in this study can be used for monitoring of health and welfare of growing-finishing pigs by detecting deviation FDB using RFID registrations. For both feeding and drinking, number of meals per pig per day is suggested to be the most suitable variable to use in generating alerts when the level is deviating from the expected level. This was based on the fact that specificity was highest for average number of meals per day for both feeding and drinking. Sensitivity of the model was hard to determine due to low number of culling cases in all batches and specific circumstances for some of the cases. In conclusion, the current model is promising for detection of health problems until seven days before the culling date in growing-finishing pigs, but further validation of the current model should occur on a bigger scale in order to increase accuracy of results and improve knowledge required for practical implication.

CRediT authorship contribution statement

B.G.C. de Bruijn: Conceptualization, Visualization, Writing – original draft, Writing – review & editing. **R.M. de Mol:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – review & editing. **P.H. Hogewerf:** Conceptualization, Investigation, Methodology. **J.B. van der Fels:** Conceptualization, Funding acquisition, Project administration, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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References

[1] J.D. Bus, I.J.M.M. Boumans, L.E. Webb, E.A.M. Bokkers, The potential of feeding patterns to assess generic welfare in growing-finishing pigs, Appl. Anim. Behav. Sci. 241 (2021), 105383, https://doi.org/10.1016/j.applanim.2021.105383.

[2] S. Pietrosemoli, C. Tang, Animal welfare and production challenges associated with pasture pig systems: a review, Agriculture 10 (2020), 223, https://doi.org/10.3390/agriculture10060223.

[3] H. Leruste, E.A.M. Bokkers, O. Sergent, M. Wolthuis-Fillerup, C.G. van Reenen, B. J. Lensink, Effects of the observation method (direct v. from video) and of the presence of an observer on behavioural results in veal calves, Animal 7 (11) (2013) 1858–1864, https://doi.org/10.1017/S1751731113001456.

[4] L. Gonzalez, B. Tolkamp, M. Coffey, A. Ferret, I. Kyriazakis, Changes in feeding behavior as possible indicators for the automatic monitoring of health disorders in dairy cows, J. Dairy Sci. 91 (2008) 1017–1028, https://doi.org/10.3168/jds.2007-0530.

[5] A. Pijpers, E.J. Schoevers, H. van Gogh, L.A. van Leengoed, I.J. Visser, A.S. van Miert, J.H. Verheijden, The influence of disease on feed and water consumption and on pharmacokinetics of orally administered oxytetracycline in pigs, J. Anim. Sci. 69 (7) (1991) 2947–2954, https://doi.org/10.2527/1991.6972947x.

[6] D.M. Weary, J.M. Huzzey, M.A.G. von Keyserlingk, Board-invited review: using behavior to predict and identify ill health in animals1, J. Anim. Sci. 87 (2) (2009) 770–777, https://doi.org/10.2527/jas.2008-1297.

[7] H.M.L. Andersen, L. Dybkjær, M.S. Herskin, Growing pigs' drinking behaviour: number of visits, duration, water intake and diurnal variation, Animal 8 (11) (2014) 1881–1888, https://doi.org/10.1017/S175173111400192X.

[8] J.A. Bigelow, T.R. Houpt, Feeding and drinking patterns in young pigs, Physiol. Behav. 43 (1) (1988) 99–109, https://doi.org/10.1016/0031-9384(88)90104-7.

[9] C. Cornou, J. Vinther, A.R. Kristensen, Automatic detection of oestrus and health disorders using data from electronic sow feeders, Livest. Sci. 118 (3) (2008) 262–271, https://doi.org/10.1016/j.livsci.2008.02.004.

[10] T.N. Madsen, A.R. Kristensen, A model for monitoring the condition of young pigs by their drinking behaviour, Comput. Electron. Agric. 48 (2) (2005) 138–154, https://doi.org/10.1016/j.compag.2005.02.014.

[11] J. Maselyne, W. Saeys, A. Van Nuffel, Review: quantifying animal feeding behaviour with a focus on pigs, Physiol. Behav. 138 (2015) 37–51, https://doi.org/10.1016/j.physbeh.2014.09.012.

[12] B.J. Tolkamp, D.J. Allcroft, J.P. Barrio, T.A.G. Bley, J.A. Howie, T.B. Jacobsen, I. Kyriazakis, The temporal structure of feeding behavior, Am. J. Physiol.Regul. Integr. Comp. Physiol. 301 (2) (2011) R378–R393, https://doi.org/10.1152/ajpregu.00661.2010.

[13] A. Alameer, I. Kyriazakis, H.A. Dalton, A.L. Miller, J. Bacardit, Automatic recognition of feeding and foraging behaviour in pigs using deep learning, Biosyst. Eng. 197 (2020) 91–104, https://doi.org/10.1016/j.biosystemseng.2020.06.013.

[14] A.L. Miller, H.A. Dalton, T. Kanellos, I. Kyriazakis, How many pigs within a group need to be sick to lead to a diagnostic change in the group's behavior?1, J. Anim. Sci. 97 (5) (2019) 1956–1966, https://doi.org/10.1093/jas/skz083.

[15] J. Maselyne, I. Adriaens, T. Huybrechts, B. De Ketelaere, S. Millet, J. Vangeyte, W. Saeys, Measuring the drinking behaviour of individual pigs housed in group using radio frequency identification (RFID), Animal 10 (9) (2016) 1557–1566, https://doi.org/10.1017/S1751731115000774.

[16] J. Maselyne, W. Saeys, P. Briene, K. Mertens, J. Vangeyte, B. De Ketelaere, A. Van Nuffel, Methods to construct feeding visits from RFID registrations of growing-finishing pigs at the feed trough, Comput. Electron. Agric. 128 (2016) 9–19, https://doi.org/10.1016/j.compag.2016.08.010.

[17] J. Maselyne, W. Saeys, B. De Ketelaere, K. Mertens, J. Vangeyte, E.F. Hessel, A. Van Nuffel, Validation of a high frequency radio frequency identification (HF RFID) system for registering feeding patterns of growing-finishing pigs, Comput. Electron. Agric. 102 (2014) 10–18, https://doi.org/10.1016/j.compag.2013.12.015.

[18] W.M. J. Eissen, E. Kanis, J. Merks, Algorithms for identifying errors in individual feed intake data of growing pigs in group-housing Appl. Eng. Agric. 14 (6) (1998) 667–673, https://doi.org/10.13031/2013.19421.

[19] T.M. Brown-Brandl, G.A. Rohrer, R.A. Eigenberg, Analysis of feeding behavior of group housed growing–finishing pigs, Comput. Electron. Agric. 96 (2013) 246–252, https://doi.org/10.1016/j.compag.2013.06.002.

[20] J. Maselyne, A. Van Nuffel, P. Briene, J. Vangeyte, B. De Ketelaere, S. Millet, W. Saeys, Online warning systems for individual fattening pigs based on their feeding pattern, Biosyst. Eng. 173 (2018) 143–156, https://doi.org/10.1016/j.biosystemseng.2017.08.006.

[21] H. Thölke, P. Wolf, Economic advantages of individual animal identification in fattening pigs, Agriculture 12 (2022), 126, https://doi.org/10.3390/agriculture12020126H.

[22] B.J. Tolkamp, I. Kyriazakis, To split behaviour into bouts, log-transform the intervals, Anim. Behav. 57 (4) (1999) 807–817, https://doi.org/10.1006/anbe.1998.1022.

[23] MATLAB and Statistics Toolbox Release 2020, The MathWorks, Inc, Natick, Massachusetts, United States.

[24] C. Chatfield, M. Yar, Holt-winters forecasting: some practical issues, J. R. Stat. Soc. D: Stat. 37 (1988) 129–140 (The Statistician).

[25] R.M. de Mol, A. Keen, G.H. Kroeze, J.M.F.H. Achten, Description of a detection model for oestrus and diseases in dairy cattle based on time series analysis combined with a Kalman filter, Comput. Electron. Agric. 22 (2) (1999) 171–185, https://doi.org/10.1016/S0168-1699(99)00016-2.

[26] S. Kruse, I. Traulsen, J. Salau, J. Krieter, A note on using wavelet analysis for disease detection in lactating sows, Comput. Electron. Agric. 77 (1) (2011) 105–109, https://doi.org/10.1016/j.compag.2011.04.002.

[27] R.M. de Mol, G. André, E.J.B. Bleumer, J.T.N. van der Werf, Y. de Haas, C.G. van Reenen, Applicability of day-to-day variation in behavior for the automated detection of lameness in dairy cows, J. Dairy Sci. 96 (6) (2013) 3703–3712, https://doi.org/10.3168/jds.2012-6305.

[28] Y. Gómez, A.H. Stygar, I.J.M.M. Boumans, E.A.M. Bokkers, L.J. Pedersen, J. K. Niemi, P. Llonch, A systematic review on validated precision livestock farming technologies for pig production and its potential to assess animal welfare, Front. Vet. Sci. 8 (2021), 660565, https://doi.org/10.3389/fvets.2021.660565.

[29] A.H. Stygar, A.R. Kristensen, Detecting abnormalities in pigs' growth – A dynamic linear model with diurnal growth pattern for identified and unidentified pigs, Comput. Electron. Agric. 155 (2018) 180–189, https://doi.org/10.1016/j.compag.2018.10.004.

[30] H.W. Barkema, M.A.G. von Keyserlingk, J.P. Kastelic, T.J.G.M. Lam, C. Luby, J. P. Roy, D.F. Kelton, Invited review: changes in the dairy industry affecting dairy cattle health and welfare, J. Dairy Sci. 98 (11) (2015) 7426–7445, https://doi.org/10.3168/jds.2015-9377.

[31] A. Nasirahmadi, O. Hensel, S.A. Edwards, B. Sturm, A new approach for categorizing pig lying behaviour based on a Delaunay triangulation method, Animal 11 (1) (2017) 131–139, https://doi.org/10.1017/S1751731116001208.

[32] A.S. Voulodimos, C.Z. Patrikakis, A.B. Sideridis, V.A. Ntafis, E.M. Xylouri, A complete farm management system based on animal identification using RFID technology, Comput. Electron. Agric. 70 (2) (2010) 380–388, https://doi.org/10.1016/j.compag.2009.07.009.