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Optimal slaughter pig marketing with emphasis on information from on-line live weight assessment

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A B S T R A C T

One of the most labor intensive tasks of a traditional slaughter pig production is weighing of pigs for marketing, and in several recent projects methods for automatic assessment of live weights are developed. For an optimal utilization of the resulting weighing data, a decision support system for optimization of the marketing policy is needed. In this paper, a pen level model intended as the core of such a decision support system for optimization of slaughter pig marketing is presented. The model is based on a hierarchical Markov process and emphasis is put on definition of the state space in such a way that the observations from the online live weight estimation may serve as input to the decision support system and thus improve the precision of the underlying predictions of future growth through a learning algorithm based on Kalman filtering in a dynamic linear model. The aim is to become able to inform the farmer on the number of pigs being ready for marketing in each individual pen. The MLHMP software system is used for implementation of the model.

1. Introduction

There is a growing need for computer-based methods for management support in pig production. Simultaneously, the possibilities for real-time monitoring of the production have improved as a consequence of modern computer technology and development of improved statistical methods. Average herd size is increasing and in the construction of new production systems one of the main objectives has been to reduce the input of human labor. The number of animals managed per person is therefore also increasing. One of the most labor intensive tasks of a traditional slaughter pig production is weighing of pigs for marketing, and in several projects methods for automatic assessment of live weights through image analysis or other automated methods are developed (Jørgensen, 2007; Rydberg and Gilbertsson, 2004; Schofield, 2007). When the equipment is installed in a production system, online estimation of live weights of the pigs is available throughout the fattening period. If those estimates are processed in an appropriate way, they serve as valuable input for prediction of growth as well. They may therefore be used as observations for a decision support tool for optimal marketing of the slaughter pigs.

The problem of optimal slaughter pig marketing can be regarded as a sequential decision problem involving decisions at two different levels: the animal level and the batch level. At the animal level decisions comprise of selecting and marketing of individual pigs based on some kind of observation of live weight, and at batch level the decision is when to terminate the batch (market the remainder of the batch and insert a new batch of weaners). At batch level, the decision is based partially on observations of the number of remaining pigs, their live weight distribution and expected growth and partially on the operational constraints of the slaughter pig unit, where the most important one probably is the weaner supply. Aspects of the problem have been dealt with before (Boys et al., 2007; Jørgensen, 1993; Kure, 1997; Niemi, 2006; Ohlmann and Jones, 2008; Toft et al.,

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2005), but the online live weight assessment is a new aspect which will be included in the present study.

A pen level model for optimization of slaughter pig marketing is presented. It is based on a hierarchical Markov process and emphasis is put on definition of the state space in such a way that the observations from the online live weight estimation may serve as input to the decision support system and thus improve the precision of the underlying predictions of future growth by means of learning algorithms based on Kalman filtering in a dynamic linear model (DLM). The aim is to become able to inform the farmer on the number of pigs being ready for marketing in each individual pen. The MLHMP software system (Kristensen, 2003) has been used for implementation of the model.

2. The monitoring system and the price system

The model is implemented independently of the online weight assessment system. It may be based on any principle (e.g. image analysis or mechanical weighing). We shall just make some assumptions concerning the output provided by the system.

The basic assumption is that if a pen with n pigs is monitored, the system is able to supply n weight estimates

$$\hat{w}_i(t) = w_i(t) + \varepsilon_{it}, \tag{1}$$

where $\hat{w}_i(t)$ is the observed weight of the ith pig at time t, $w_i(t)$ is the true live weight, and $\varepsilon_{it} \sim \mathcal{N}\left(0, \sigma^2\right)$ is the measurement error, where we assume that the precision (i.e. $1/\sigma^2$) is known. It must be emphasized that the pigs are not identified. We only know that the observed weight distribution is given by $\hat{w}_1, \ldots, \hat{w}_n$. We are not able to identify a particular weight estimate with a specific pig. Note, that through the weight estimates we are also able to answer questions of the type: "How many pigs in the pen have an estimated weight higher than δ?" This is important for the implementation of a delivery policy based on threshold weights as described later.

In Denmark the price obtained for a slaughter pig depends on the slaughter weight, where the highest price per kg is obtained in a range around 77 kg. For higher as well as lower slaughter weight the price is reduced proportionally with the deviation from the optimal interval. Furthermore, there is a price reduction for lean meat percentages below 61 and a premium for higher percentages. Since neither the slaughter weight nor the lean meat percentage is observable by the farmer, the decision to deliver pigs for slaughter is made on the basis of observed live weight and observed growth rate. Thus, the decision is made under uncertainty concerning slaughter weight and lean meat percentage.

3. Biological model

3.1. Modeling live weight over time for slaughter pigs

In order to describe the growth of the pigs in a specific pen, we use a dynamic linear model (DLM) with Kalman filtering as described by West and Harrison (1997).

We shall assume that an average growth curve $\bar{y}(t)$ has been estimated from herd specific data. In the weight interval relevant for slaughter pigs, the average curve is more or less linear, but we shall not in this paper make any specific assumptions concerning the shape of the growth curve. It is just assumed that a known herd specific growth curve $\bar{y}(t)$ exists. Even though the general curve is known, the growth potential of the pigs in a particular pen may deviate from the average value given by $\bar{y}(t)$. To be more specific, we assume the true weights $w_i(t)$ to be distributed as $\mathcal{N}(\bar{y}(t)L, \sigma_w^2)$, where L is a scaling factor related to the pigs currently occupying the pen. The value of L is in principle unknown, but the initial belief is that the true value is distributed as $\mathcal{N}(1, \sigma_L^2)$, where σ_L reflects the variation between pens. As observations are obtained for the pen, we may update our belief in the true value of L. Even though the true mean of $w_i(t)$ is assumed to be $\bar{y}(t)L$, the average value of the true live weights (i.e. $\bar{w}(t) = (\sum_i w_i)/n$) will deviate from that value because of the sample uncertainty. We may express this as

$$\bar{w}(t) = \bar{y}(t)L + e(t) \tag{2}$$

where $e(t) \sim \mathcal{N}\left(0, \sigma_e^2\right)$ represents the sample uncertainty. If we further add the measurement error we obtain the following observation equation for the DLM:

$$\hat{\bar{w}}(t) = \bar{y}(t)L + e(t) + \bar{\varepsilon}_t. \tag{3}$$

The true value of L is assumed to be a permanent trait of the present group of pigs, but as concerns the sample uncertainty $e(t)$, it is assumed to be autocorrelated over time. If we, for instance, assume weekly intervals, we have

$$e(t) = \alpha e(t-1) + \eta_t \tag{4}$$

where α is an auto regression coefficient, and $\eta_t \sim \mathcal{N}\left(0, \sigma_\eta^2\right)$ is an independent random term. Eq. (4) will be one of the system equations of the DLM.

As described so far we have only used the average observed weight as a source of information. Since we have actually observed $\hat{w}_1, \ldots, \hat{w}_n$ we have much more information available about the distribution. We could for instance calculate the sample variance, but the problem is that the distribution of the sample variance is not normal. It is therefore difficult to include it in a DLM. Instead we shall use the 0.16 sample quantile $\hat{w}_{(0.16)}$ as a further description of the underlying distribution of live weights. Since the distribution of a sample quantile is (asymptotically) normal around the true quantile, we have

$$\hat{w}_{(0.16)}(t) = \bar{y}(t)L + e(t) - \rho(t) + \tau_t \tag{5}$$

where $\rho(t)$ is the standard deviation of $\hat{w}_i(t)$, and $\tau_t \sim \mathcal{N}\left(0, \sigma_\tau^2\right)$ expresses the sample uncertainty. In Eq. (5) we use the well known fact that in a normal distribution, the 0.16 quantile is the mean minus the standard deviation. With a rather limited number of pigs in a pen, the exact 0.16 quantile is difficult to observe, so in practice the n observed weights are sorted, and the kth order statistic is selected as the observation, where k is the integer making the fraction $(k-1)/n$ "close to" 0.16. Since, it is not likely, that $(k-1)/n$ is exactly 0.16, $\rho(t)$ must be multiplied by an adjusting factor a close to 1 in Eq. (5). The factor only depends on the values of n and k, and it is easily determined from the properties of a normal distribution. If, for