MODELING THE CAUSES OF LEG DISORDERS IN FINISHER HERDS

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SUMMARY

We present a probabilistic model that estimates the probability distributions of different manageable causes of leg disorders in finisher herds. The purpose of the model is to identify the probability distributions of three cause-categories of leg disorders: Infectious, Inherited and Environmental. The probabilistic model is constructed using an Object-Oriented Baysian Network and the parameters in the model are based on published literature and expert opinions. The objects of the model are instances of two classes (herd -and pig class), each contributing with information to the model. The probability distributions can serve as a consistent set of inputs for economic calculations.

Keywords: object-oriented Bayesian Network; finisher herds; leg disorders; economics

INTRODUCTION

Leg disorders in finisher herds cause economical losses for the farmer. The losses are due to reduced productivity (e.g. decreased daily weight gain), medical treatment costs and increased work load due to the physical handling of the pigs. Furthermore, leg disorders are also an indication of poor animal welfare. Leg disorders in finishers can conveniently be divided into three major cause-categories: Infectious, Inherited and Environmental. Infectious leg disorders represent arthritis caused by infectious agents such as *Mycoplasma hyosynoviae, Erysipelothrix rhusiopathiae, Haemophilus parasuis and Streptococcus sp*. Osteochondrosis can be characterized as an inherited leg disorder and is a disturbance in the endochondral ossification of the cartilage and bone (Grøndalen, 1974). Environmental leg disorders represent injuries to the limb and claw such as fractures and claw lesions.

Control strategies against leg disorders will depend on the cause-category. Thus, antibiotic treatment will be used against infectious arthritis whereas improvement in the pen and floor construction will be the strategy against environmental leg disorders. In order to implement the optimal control strategy for leg disorders in a herd it is essential to know the most prevalent cause-category. The purpose of this paper is to create a probabilistic model that can estimate the probability distributions of different manageable causes of leg disorders in finisher herds.

METHOD

Object-Oriented Bayesian Network

The probabilistic model for leg disorders is constructed using an Object-Oriented Bayesian Network. In this model the objects are instances of two classes: the herd class and the pig class.

The object is the basic component in the object-oriented paradigm and each object has entities with identities, states and behaviour. The two classes represent objects that share the same structure, behaviour and attributes (Bangsø, 2004). The herd class has one object with a number of entities (e.g. the stocking density of pens and the herd size). The pig class is used to create several objects and each object has entities representing animal specific information (e.g. clinical signs of lameness, gender and results from diagnostic tests). The object-oriented paradigm is included in the framework of a Bayesian network. Hence, the model is a static model for a single herd and all interdependencies are described using conditional probability distributions. The model is a directed acyclic graph where the directions of the links represent the biological causalities. The Bayesian network allows information to flow in the opposite direction of the causality (Jensen, 2001). Each node in the model is discrete and represents a finite number of states. Input to the model is the state of the various risk factors or diagnostic tests. A few nodes in the model are latent nodes which are not directly observable but help in the specification of the model. The major outputs of the model are the pressure of the three cause-categories of lameness at herd level. These nodes are considered to be continues, however, due to properties of Bayesian networks we make a discretization of the nodes.

The structure of the biological model

The background for the qualitative structure of the model is based on evidence from the literature as well as information from experts (literature references are not included in this paper). For the herd class, evidence regarding the nodes: *Production* (sectioned or continues production), *Purchase* (number of suppliers) and *Herd size* (number of pigs slaughtered annually) will influence the probability distribution for infectious arthritis. However, the nodes: *Floor* (floor type in the pen), *Straw* (use of bedding) and *PenDen* (stocking density in the pen) will influence the probabilities for all three cause-categories. The breed as well as the weight gain will affect the occurrence of inherited leg disorders.

It is the intention that a number of pigs in the herd can be selected randomly and observed for clinical signs of lameness. Evidence on whether or not the selected pig shows clinical signs of lameness is included in the node *ObsLame*. The true state of lameness for the individual pig is presented in the latent node *PigLame* and the relation between the two nodes: *PigLame* and *ObsLame* depend on the sensitivity and specificity of the clinical observation. Based on diagnostic tests (e.g. pathological and bacteriological tests) as well as further information regarding the individual pig (e.g. tail bite, gender and lean meat percentage) it is possible to estimate the probability distributions of the specific lameness diagnoses. Hence, each object in the pig class will provide evidence regarding clinical signs of lameness, and for the lame pigs it is further possible to specify the most likely lameness diagnosis (e.g. fracture, claw erosion). The individual lameness diagnoses will add information to the probability distributions of the cause-category of lameness at herd level.

Data to the model

The study uses results from a large number of published papers in order to quantify the conditional probability distribution between any two nodes. Where no quantitative information exists we take advantage of expert opinions. However, in some situations we have quantitative information about nodes that are not directly connected with a link in the model. For instance, it is possible to estimate the conditional probability distribution between *Weight* and *OCD* (osteochondrosis dissecans) based on information from the literature. However, what we need to specify in the model is the conditional probability distribution between *Weight* and the cause-category: *Inherited*. Using the Markov property of a Bayesian network it is possible to move directed edges from where we have the quantitative information to directed edges that represent the causality in the model (Otto and Kristensen, 2004)

RESULTS AND DISCUSSION

The Object-Oriented Bayesian Network model presented in this paper estimates the probability distributions for three cause-categories of lameness in finisher herds based on evidence from two classes. The biological structure of the model is shown in Figures 1–3 and a description of each node, including the node type and the states, is shown in Tables 1–2.

Using evidence from the herd class only, it will be possible to estimate the probability distributions of the three cause-categories. However, by including information from the pig class, it will be possible to obtain further knowledge and reduce the uncertainty about the cause-category of lameness in the herd. Previously, a Bayesian network model describing the infection with *Mycoplasma hyopneumoniae* in swine herds has been developed (Otto and Kristensen, 2004). In that study only herd-specific risk factors were included in order to estimate the probability distribution of the severity of infection. The differential diagnoses for lameness presented in this model are not fully complete and it is possible for pigs to have clinical signs of lameness due to other aetiologies (e.g. nerve compression and muscle rupture). However, we believe that the lameness diagnoses presented in this model are the most common in Danish finisher herds. Published research results as well as expert opinions form the basis for the qualitative and quantitative structure of the model. However, we have not taken into account the fact that the evidence used in the calculation of the conditional probability distributions, can be associated with uncertainty.

This model is the first step in developing an economic model for leg disorders in finisher herds. Hence, the probability distributions for the different cause-categories of leg disorders can successively serve as a consistent set of inputs for economic calculations of the effects of alternative control strategies against leg disorders in finisher herds. More work is needed to complete the quantitative part of the model presented in this paper.

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Table 1. Nodes in the herd class

Node name	Node type	Explanation	States
PenDen	Input node	The stocking density of pens	High/Low
Floor	Input node	The type of floor in pens	Solid/Partially slatted/Totally slatted
Straw	Input node	Supply of straw to pens	Deep bedding/Sparse bedding/No bedding
Herd Size	Input node	Number of pigs slaughtered annually	1-1000/1001-3001/3001-5000/5000-
Production	Input node	Type of production in the herd	Sectioned/Continues
Purchase	Input node	Number of farms that supply piglets to the herd	Zero/One/More than one
Breed	Input node	The breed of pigs	Landrace/Yorkshire/Duroc
FeedStrat	Input node	The feeding strategy	Ad libitum/Restricted
Weight	Input node	Average daily weight gain of pigs in the herd	700g/800g/900g/1000g
Environmental	Output node	Measure of the environmental causes of leg disorder in the herd	1–10
Infectious	Output node	Measure of the infectious causes of leg disorder in the herd	1–10
Inherited	Output node	Measure of the inherited causes of leg disorder in the herd	1–10

Table 2. Nodes in the pig class

Node name	Node type	Explanation	States
Fracture	Latent node	Fracture of the limb or claw	Yes/No
ClawErosion	Latent node	Erosion to the heel, toe or sole	Yes/No
ClawLesion	Latent node	Lesion in the white line or side wall of the claw	Yes/No
Myco	Latent node	Mycoplasma hyosynoviae	Yes/No
Strep	Latent node	Streptococcus sp.	Yes/No
Erysi	Latent node	Erysipelothrix rhusiopathiae	Yes/No
Haemo	Latent node	Haeomophilus parasuis	Yes/No
OCM	Latent node	Osteochondrosis manifesta	Yes/No
OCD	Latent node	Osteochondrosis dissecans	Yes/No
Gender	Input node	Gender of the pig	Castrate/Female
MeatPercent	Input node	Lean meat percentage (increase in percent points)	0/1/2/3/4/5
TailBite	Input node	Tail bite	Yes/No
Arth_Risk	Latent node	Risk of arthritis	Yes/No
PigLame	Latent node	True state of the clinical lameness	Yes/No
Obs_Lame	Input node	Observation of clinical signs of lameness	Yes/No
Clinic1	Input node	Results of the clinical examination of ClawLesion	Yes/No
Clinic2	Input node	Results of the clinical examination of ClawErosion	Yes/No
Bac1	Input node	Results of the bacteriological examination of Mycoplasma hyosynoviae	Yes/No
Bac2	Input node	Results of the bacteriological examination of Streptococcus sp.	Yes/No
Bac3	Input node	Results of the bacteriological examination of Erysipelothrix rhusiopathiae	Yes/No
Bac4	Input node	Results of the bacteriological examination of Haeomophilus parasuis	Yes/No
Path (1; 9)	Input node	Results of the pathological examination of the leg or joint. One node for each of the nine lameness diagnoses	Yes/No

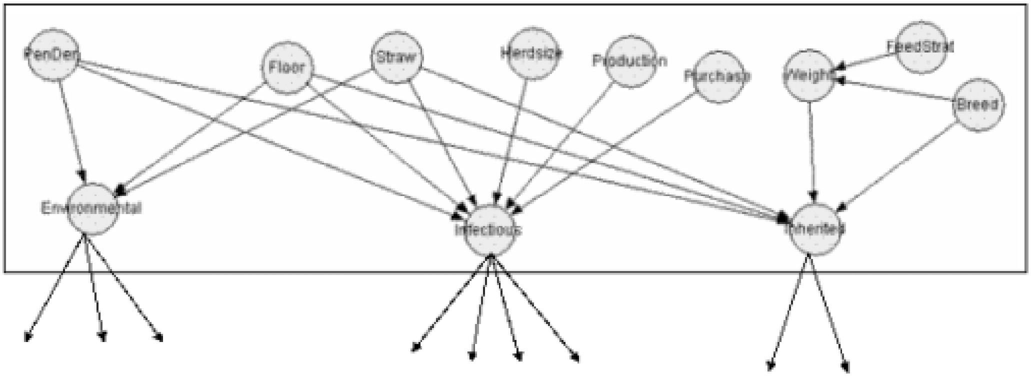

Figure 1. The herd class

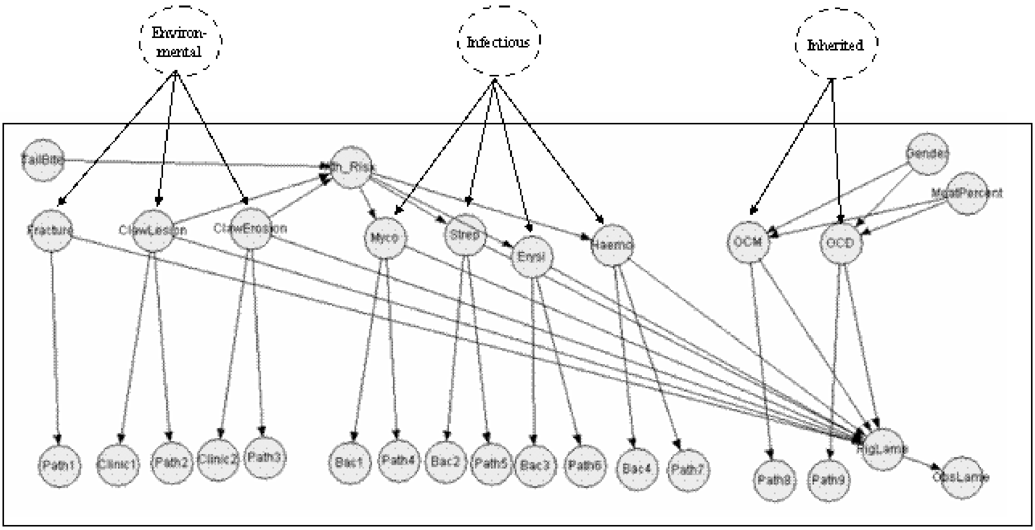

Figure 2. The pig class

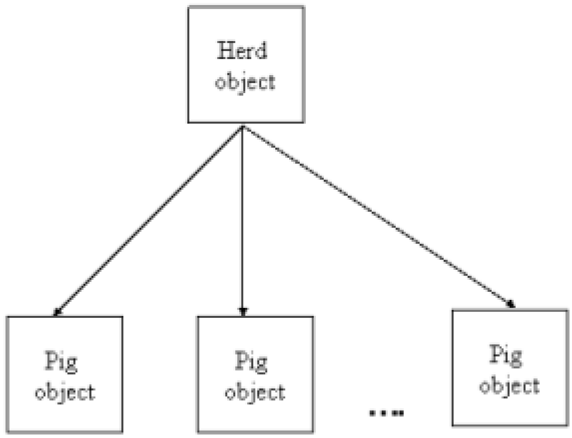

Figure 3. The relation between objects in the herd class and the pig class