TRADEOFF'S IN MODELING EPIDEMIC DISEASE IN SLAUGHTER PIG PRODUCTION.

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ABSTRACT

Model based decision support for optimizing the decision complex stemming from a slaughter pig production exposed to infectious disease requires careful analysis of the individual components and their modeling. Due to limitations imposed by existing methods and computational considerations the resulting model will be a tradeoff between modeling the conceptual aspects and the possibilities within the selected framework. Here we discuss the development of a model based decision support system for simultaneous optimization of decisions regarding disease control and marketing pigs for slaughter in a slaughter pig production unit.

INTRODUCTION

In recent years several decision support systems for managing epidemic disease have been developed. However, most systems seem to implicitly assume that the disease in question requires immediate response in the form of some predefined control measure. For a large group of diseases this is a valid assumption. Control of diseases such as Classical Swine Fewer is often carried out by means of stamping out affected herds. Decision support systems for handling the highly contagious diseases rarely seek to optimize the decisions related to control of disease, but merely serve as a Management Information System. The various flavors of the EPIMan system are examples of this kind of system. The associated InterSpread simulation models are then applied to simulate "what-if" scenarios of applying different controls, given the current information regarding the epidemic. The decision whether to apply the stamping-out or not are rarely considered in practice since the economic impact of these highly contagious diseases is too severe to experiment with alternative suggestions. The problem of missing alternatives is essentially the same in diseases such a clinical mastitis. Here, the farmer is given the choice to cull the cow or treat her. Keeping an untreated cow is usually not a considered option. Thus, from a modeling point of view mastitis can be regarded as just another trait of the animals when optimizing replacement decisions (Houben et al., 1994).

Swine Influenza is an example of a disease that does not comply with the above methods. Currently there is no vaccine (in Denmark) for Swine Influenza. Still, if a vaccine was available it could be questioned whether or not to apply it. The choice would be entirely the farmer's; hence a decision support system should seek to produce an optimal strategy for control of the disease. The disease, however, is no longer the primary (or at least only)

concern. Swine Influenza is usually not fatal. The common effect is loss of appetite, which causes reduced feed intake, hence lower the daily gain. When considering appropriate control strategies for this kind of disease it seems that this requires a simultaneous optimization of the overall objective of the slaughter pig production: to maximize the return from the production facility.

This paper discusses the elements of a model based decision support system to optimize the decision complex emerging from selecting and delivering pigs for slaughter, when exposed to epidemic disease such as Swine Influenza. The resulting model is a tradeoff between modeling the individual elements and existing techniques. When adopting the model despite the identified shortcomings of its framework, the effect of these problems should be addressed.

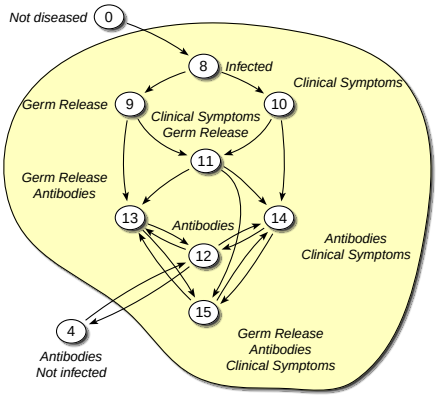
MODEL ANALYSIS

Here we briefly outline the components of the model developed in Toft et al. (2001). The model is constructed in the framework of *multi-level hierarchic Markov processes* (Kristensen & Jørgensen, 2000). This enables simultaneous modeling and optimization of decisions at multiple time scales using an infinite time horizon. To see why these properties are necessary requirements of our modeling framework, consider the decision complex of delivery actions and control strategies. The selection and delivery of pigs for slaughter is carried out at the daily operational level, i.e., the decision to deliver certain pigs in a given week is based on assessment of their weight in that week. Other decisions regarding the production system such as, e.g., the interval between start of new batches are usually of a more strategic character. Due to the general inertness of the pig production, changes in e.g. weaner supply are slow to adapt to a new housing policy. Hence, the model discussed here implicitly assumes that the production is an *all-in all-out* production where a new batch of, e.g. 200, weaners is inserted every 16 weeks. The optimal delivery policy seeks to deliver the pigs in a batch at optimal delivery weights while considering the possible benefit of premature emptying the section to reduce the disease pressure imposed on the next batch. However, the optimal delivery policy must depend on the control measures adapted so far, i.e., observing a few sick pigs in a vaccinated population might not be as worrying as in an unvaccinated population where such an observation could call for delivery of all pigs to avoid the expected reduction in daily gain associated with the disease. The model operates with two different kinds of control measure: preventive and treating. The difference lies in the time of application. The preventive measures such as vaccine are carried out at the beginning of a batch or at least prior to observing disease. The effect of a vaccine is assumed to last the lifetime of a slaughter pig. The treatment of pigs by, e.g., administering medicine is usually only carried out when sick pigs are observed in the section.

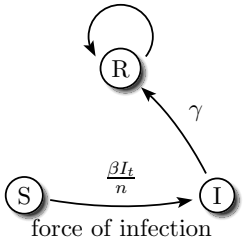
Our task is simultaneous optimization of the high level decisions regarding vaccine and the daily operation involving medicine and delivery actions. To devise an optimal policy for this decision complex, models for growth of the pigs, spread of disease among pigs in the section, and transmission of disease pressure between successive batches are needed. Below we sketch the models for disease spread among individual animals and between batches. The growth model simply assumes a constant daily gain with a reduction due to disease.

DISEASE MODELS

Consider Figure 1(a) (c.f. Jørgensen et al. (1995)) as a possible model of the stages that an animal passes through during the course of a disease. Starting at the stage of initial exposure to the infectious agent (i.e., stage *Not diseased*), through the stages of infected, germ releasing etc. until finally the animal is no longer affected or infectious.



(a) The disease model from Jørgensen et al. (1995)



(b) The SIR model

FIGURE 1 The disease model from the simulation study and the SIR model used here.

The model in Figure 1(a) reflects how disease might develop within a pig. However, our main concern is how disease might develop among pigs, i.e., the epidemic. For this purpose the model in Figure 1(a) is far too complicated to elaborate on. Instead we turn towards a simpler, but widely accepted model known as the General epidemic, introduced in its stochastic form by Bartlett (1949). In the General epidemic model all animals are assumed initially susceptible for infection by disease. After infection they become infectious for a period, then stop being infectious, recover and become immune. Since the animal, in turn, pass through the stages of susceptible, infective and recovered/removed we will refer to the model as a SIR-model. Using a SIR-model, the spread of an infectious disease in a population of homogenous animals who mix uniformly, is modeled as a Markov continuous-time model. The transition in this model is visualized in Figure 1(b). The force of infection is the rate, at which a susceptible animal becomes infected, i.e., $\beta It/n$. The parameter γ express recovery rate.

The estimation of parameters β and γ can be accomplished in various ways. However, it is often the case that only the final state of the epidemic is known, hence estimation is carried out without any real knowledge of the infection process, the time of first infection etc. Methods that account for the missing information do exists see, e.g., Becker (1989), O'Neil & Roberts (1999).

Another path towards estimates of parameters for the SIR-model is through simulation studies. This way we can account for different aspects of the production system such as confinement and herd size and their influence on the parameters in question. The simulation model outlined in Jørgensen & Kristensen (1995) has been extended to include disease using the model from Figure 1(a). Within this simulation framework it is possible to merge the results of case studies and expert opinion. Calibrating the model based on input-output analysis has been formalized in Jørgensen (2000). The analysis in Jørgensen et al. (2000) shows that the reduction from the simulation model to the SIR model is somewhat problematic, since most diseases feature an incubation period in which the animal is exposed to disease but not yet infectious. This corresponds to a SEIR-model where the pigs, in turn,

pass through the stages of Susceptible, Exposed, Infective and Recovered. We shall return to this issue in the discussion.

To produce an optimal policy based on the observed number of diseased pigs we require the transition from each possible configuration of susceptible and infectious animals at one decision stage to the next. Direct application of the SIR-model in its discrete representation would require enormous storage capacity and computations even for moderate sized populations of, say, 200-400 pigs per section. Hence a parametric approach based on a Normal distribution approximation to the state-space has been applied (Isham, 1991).

The SIR-model addresses the evolution of epidemics within each batch. The second element of the disease spread model addresses the transition of disease pressure between batches. This is used to model the risk of the initial exposure to disease, i.e., the first infected pig in a section is assumed to contract the disease from an exogenous source. It seems reasonable to assume that the previous as well as parallel batches occupying the remainder of the production system contribute to the risk of initial infection. Define φ as the transition intensity from S to I in absence of diseased pigs in the current batch. Using φ we will determine the corresponding probability p01 of introducing a sick animal between 2 decision epochs, e.g., from one day to the next. It seems reasonable to assume that the waiting time to introduction of disease is exponential, hence within a batch $p01 = 1-\exp(\varphi)$. The model for transmission of φ between batches is chosen as an autoregressive process with an increase in intensity by the proportion of sick pigs and a decrease in intensity by early emptying of the pen.

In the multi-level hierarchic Markov process framework the model outlined here is defined at two levels. The founder level models the transition between successive batches. The states at the founder level represent a discrete representation of the reasonable range of transition intensity (φ). The actions at the founder level regard decisions such as vaccination. Each combination of state and action of the founder process spans a child process representing an individual batch of slaughter pigs. This process consists of a stage for each day prior to delivery and a stage for each delivery day. The states of an ordinary day are the possible configurations of susceptible and infectious pigs. The states at each delivery day are the same for each of different number of pigs still left in the section. Actions at this level includes whether or not to administer medicine and if delivery is possible, how large a fraction to select for delivery. The objective of the optimization is to produce a policy that maximizes the expected discounted net return of the section. A policy is a decision-rule for each possible configuration of founder-level state and child-process stage and state.

DISCUSSION

A model like the above is not intended for direct application on a slaughter pig farm, but may serve as a useful tool for knowledge acquisition concerning the interactions among the different decisions in the system. Thus, the model could be applied to evaluate the possible cost-benefit of applying a certain vaccine in a particular production. Preliminary results show the expected relationship between vaccine cost and disease pressure, i.e., the higher the risk of disease, the more the farmer should be willing to pay for vaccine. The delivery policy also regards the number of sick pigs when determining the ratio of pigs to deliver for slaughter. In early stages of the epidemic the section is emptied prior to the optimal time in absence of disease. The effect is dual: the associated reduction in daily gain is avoided and the transmission of disease pressure to the next batch is reduced. It seems from the results in Toft et al. (2001) that avoiding reduced daily gain is the most important reason for emptying the section early. We shall refrain from further discussion of the possible benefits of the model

and direct attention towards some of the assumptions we have made in order to model using the multi-level hierarchic Markov process framework.

The objective of the optimal policy is not to eradicate the disease, but to maximize the profit. This suggests that first priority is given to modeling the production system itself. A slaughter pig production can be regarded as an infinite sequence of successive batches of pigs each occupying the same space. Hence the objective is to optimize the return of this production system. Here we model only one section, however, usually a slaughter pig production consists of several parallel sections where pigs are inserted, say, every fortnight. Since we abstain from optimizing the production system itself, these parallel sections primarily contribute to considerations regarding disease pressure. This effect should be further explored in future studies. For now we focus on the choice of epidemic model and the underlying assumptions.

The multi-level hierarchic Markov processes require full observability of the system traits influencing the decision process. Hence we assume that the state (i.e. the number of susceptible and infectious pigs at a given time) of the epidemic is known with certainty. However, in real life this is a questionable assumption: the true herd health status can only be assessed through testing and usually there is a strong correspondence between the cost of a test procedure and its precision. Thus the difference in value between actions that are based on the observed number of sick pigs and crude rules-of-thumb should be weighed against the cost of providing the necessary information.

The question of SEIR vs. SIR models is more or less the same problem. The exposed stage of the epidemic is essentially unobservable; hence a SEIR-model would make little sense in the multi-level hierarchic Markov process framework. Simulation studies show that the shorter the incubation time, the better fit of SIR (Jørgensen et al., 2000). This suggest that analysis can be carried out using diseases with short incubation times to justify the choice of SIR. Even so, the problem of imperfect knowledge regarding the true state of the epidemic still needs to be addressed when interpreting output from the model. The implications of not knowing the precise number of sick pigs becomes evident when considering the optimal policy for issuing medicine based on observed number of sick pigs at a given day. Figure 2 shows policies at different medicine costs for the scenario in Toft et al. (2001). Even for moderate medicine prices therapeutic action requires rapid response. However, this implies that high precision in the observation method is needed to ensure a high probability of early detection of disease.

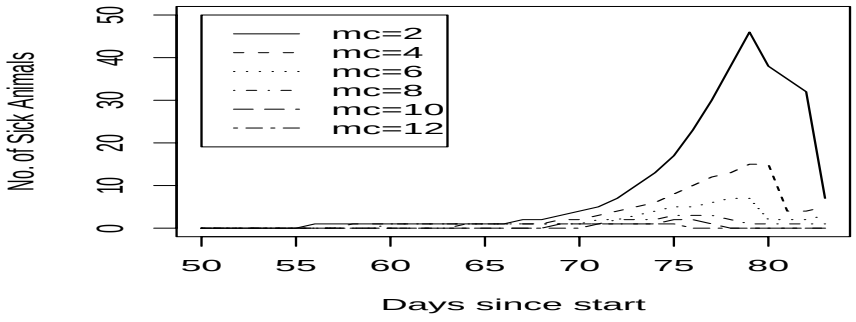


FIGURE 2 The threshold curves for applying the medicine at a given day for a given medicine cost (mc). Only when the number of sick pigs (in a section of 200) for a given day lies below the curve is medicine profitable at the specified cost.

This supports the claim often made by veterinary epidemiologists that the effort to prevent disease should occur much earlier, e.g. prior to onset of disease. This favors actions like vaccination and "fire-walls", i.e., constructions in housing to prevent disease spread. It is unlikely that the disease used here could justify the cost of the latter, but further analysis could explore this. The problem is that while vaccine is more or less specific to the individual disease, housing affects all disease. This implies that the disease model needs to be extended to account for several diseases to explore these benefits. Since several of the mild epidemic diseases are due to virus for which therapy is useless or unavailable it seems that the problem of poor medicine policies can be somewhat ignored. Hence we are left with the outline of a tool for cost-benefit analysis of vaccine programs for diseases of certain characteristics. Further studies are needed to quantify the effect of shortcuts and assumptions underlying the model.

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