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REVIEW OF MATHEMATICAL MODELS FOR SOW HERD MANAGEMENT

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Abstract

This paper is a survey of different sow models described in literature, which made use of different mathematical methodologies, and were intended for sow herd management. Models were discussed under a wide classification, that is, simulation and optimisation. The last included linear programming and dynamic programming with Markov decision models and optimal control as major representative models. In a first stage we recalled general traits and modelling foundations of herd management models and later, different aspects of sow herd models published up to now were reviewed. Special attention is paid to main variables, source of parameters, validation, output and intended use. Most of such models have been developed as research tools and teaching aids. Actually, the increasing ability to represent complex systems is not corresponded with an augmentation of decision support tools including such complex models in field conditions. Thus, a need of new proposals dealing with transient situations and non-time homogeneous parameters was detected. The inclusion of variability risk features and multicriteria decision methods were also of interest for practical purposes. Actual changes in the pig sector leads to expect new management herd models, in particular considering more than one herd at a time.

Key words: modelling, sow, herd management.

1. Introduction

Swine production has changed a lot during the last decade within the European Union (EU), and it is expected to change even more. Due to recent enlargement of EU, regulations concerning pig welfare, competition and continuous growth of the census, there has been increasing concern about the measurement and comparison of resulting management strategies in sow farms. Furthermore, the future of swine producers will depend on their ability to enhance their economic performance by improving productive efficiency rather than increasing farm size. Therefore, sow herd management models can play an important role to optimise management alternatives or to explore new ones. However, a critical revision of proposals made up to now seems to be adequate for adapting them or making new contributions for future developments.

Herd management is the process by which certain goals of the farm manager, expressed as amount of product, are achieved by consuming a corresponding amount of production factors. In order to be able to combine these factors in an optimal way it is necessary to know the main interrelations among them and their influence on the final productivity of the system. It is usual to make system simplifications in order to get practical herd models although conserving the essence of the real system. The challenge of the livestock modeller is to represent what is essential in the system in order to find relevant answers from a problematic situation that may initially seem chaotic.

Mathematical models representing the production behaviour of a livestock herd have been used for a long time in livestock research and development. Livestock herd models, in general, and sow herd models, in particular, are important tools to analyse different herd management strategies. Here, a sow herd model is defined to be a model which mimics a group of breeding animals replaced periodically over time. Through herd models, researchers first, and swine specialist and farm managers after, can better understand real farm behaviour and manage it. Researchers have had the benefit of advances in computing, database and solving software which have enabled farming systems to be described in greater detail and with greater ease (Kingwell, 1996). For instance, programming models published in the 70's dealt with hundreds of states, and in the 90's the number raised up to several millions of them (e.g. Houben et al., 1994). Moreover, methodological improvements have been done to represent fairly the system and thus, results have been obtained in solving or circumventing problems related to complex models (e.g. Kristensen, 1988, 1991). Nevertheless, research models are usually quite complex in connection with the system represented and they become less effective for practical use as yet. Despite the fact that the ultimate objective of model building in sow herd management should be to improve decision making, few models are used by specialists and advisers, even less by farmers. Actually, the increasing ability to represent complex systems is not corresponded with an augmentation of farm manager's demand of computerised decision support tools including such complex models (Kamp et al., 1999).

The objective of this paper is to review existing sow herd models representing the productive and reproductive behaviour of a group of breeding sows over time and their mathematical foundation. Hence, the use of such herd models is mainly focused on reproduction and replacement management of sows whilst other management aspects are left out of consideration. It is in the aim of this review to detect strong and weak points making models more or less suitable for practical use. This review is intended as a contribution to help the development of more practical and reliable tools for on farm sow decision support.

2. THE MODELLING OF SOW HERD MANAGEMENT

2.1 A sow herd as a system

The sow herd system can be understood as a set of different interrelated elements, i.e. breeding-animals, that acts as a whole face to exogenous solicitations. Modern piglet production is carried out under intensive methods which have proven to be more effective than traditional ones. Important aspects involved in this activity are piglet production, the provision of feedstuffs or concentrates, breeding, sow replacement and waste disposal which may have a significant impact on system performance (Glen, 1987).

The modelling of sow herd management has to represent main traits of the sow farm operation. Thus, the lifespan of a sow usually starts when it is purchased or reared as a gilt and introduced on farm after a recommended quarantine (Figure 1). Weight, age and observed heats are parameters to take into account when mating gilts for the first time. In general, gilts and sows are supposed to be ready for mating when heat is detected. For gilts there are different breeding strategies such as mating them at second or third heat. Main breeding techniques involve natural mating and artificial insemination. The management of sows in herd batches has been widely used for many years in order to schedule farm operations more easily, although individual management is also possible, even more in small farms. After mating, gilts and sows are controlled in order to detect and confirm pregnancy. When conception has failed, sows go into heat again in the next oestrus cycle and therefore, they could be mated once more or rejected as unproductive. Instead, if conception is successful, the gestation period can lead to farrowing or to an abortion. After farrowing, piglets remain with the sow for several days during the lactation period until the weaning. Fostering is also possible and it can represent a shorter lactation for sows. Other lactation/weaning systems, less frequents, more complex and refined are possible, e.g. the Isowean system. After a regular lactation, litters weaned are moved to the nursery facility or sold. Weaning and abortion represent the two regular ways that a reproductive cycle can finish. Therefore, within the herd, the basic production unit is a female pig and herd production, measured in the number of piglets weaned/sold or in Kg of live weight sold, is intimately related with the reproduction process. Male animals are also essential to the reproductive process but artificial insemination is increasingly used for breeding intensive livestock and boars can be neglected at commercial level. More important is the role of boars when quality aspects are dealt with. For instance, those related with genetic traits that can involve important decisions in breeding herds.

>>>> Insert Fig. 1

2.2 Main mathematical methodologies applied in livestock herd modelling

2.2.1. Some background on livestock herd modelling

A mathematical model is a system representation in terms of logical and quantitative relationships assuming a trade-off between accuracy and tractability. Different mathematical livestock models have been published, but swine production has received relatively little attention. For instance, see Glen (1983) and Kennedy (1981) for a general overview of livestock herd modelling or Jalvingh (1992, 1993) and Kristensen (1993) for a restricted review of dairy and sow herd models focused on reproduction and replacement management.

Livestock herd models have the female animal in common as a production unit. The herd is represented by either individual females or a group of independent and identically distributed females in most of the cases. Hence, to cope with the discrete event nature of the reproduction process the sow's lifespan is split into different reproductive states which are bounded by events as shown in Figure 1 (e.g. gestation bounded by fertile mating and farrowing, lactation bounded by farrowing and weaning, etc). The assessment of production efficiency requires the consideration of the effects of herd structure and dynamics on the calculation of productivity measures. All approaches to herd management attempt to capture the herd dynamics in some way. This is central to model the performance of intensive livestock herds in which production is not homogeneous over time, it is mainly affected by the age (or parity level instead) of breeding animals. Then, herd dynamics is derived from the flow of animals through states and is affected by voluntary and involuntary culling. Final production is determined by the number of cycles performed and the cumulative yield of each herd unit. In this way, Upton (1993) identified reproduction, mortality and yield as the main components of performance in livestock systems.

Methodologically herd models can be classified in simulation and optimisation models. In general, simulation models are well suited to dealing with the variability and complex nature of livestock production, while optimisation models have an objective function of expected utility or profit that is maximised subject to production alternatives, prices and resources availability. On the other hand, simulation models are intended to gain insight into the livestock system, i.e. to be run, whilst optimisation models are just solved to determine optimal strategies or outcomes.

2.2.2. Simulation models

Simulation models are flexible with regard to initial state, time horizon, discount rate, management strategies and stochasticity (Baptist, 1992). They can be classified under different criteria: (i) by random elements, deterministic versus stochastic; (ii) by simulation time step, discrete event versus continuous and (iii) by inclusion of time as variable, static versus dynamic. Simulation of either the deterministic or stochastic kind can be useful to study the average outcome and its dispersion over time. However the common drawback is the confusing multitude of possible outcomes. Deterministic simulation is understood in the sense that the same set of inputs performs the same result, so, it can not provide estimates on variability related to the final result. As the reproduction process plays an important role in herd management, then, event driven simulation appears to be advantageous as against continuous time models. The simulation of discrete events is controlled by pseudorandom number generators and suitable probability distributions. Almost all simulation models are themselves described as a partially stochastic in order to express that not all the parameters are determined randomly. Furthermore, some stochastic models use pseudorandom number generators not only for discrete events simulation but also for some continually distributed variables like live weight changes, litter size and milk production. As a result of using random numbers, multiple runs are needed to obtain a reliable confidence interval of the average results of the herd. However, distributions for each parameter are not always known, therefore uncertainty is approached stating first an “a priori” distribution and performing later risk analyses, quite often in an equivalent static framework (Pannell et al., 2000). When time is not included as variable, the model is considered static, otherwise it is dynamic.

2.2.3. Optimisation models

Usual optimisation methods employed in livestock modelling are linear programming and dynamic programming. The last include both, discrete time models as Markov decision processes and continuous time or optimal control models. The common trait is that they are intended to solve a well-defined problem in the best way. Frequently, optimisation models are static models because time is not considered or it simply plays no role (that is the case for the so-called stationary models). Static models abstract from the situation following a change and assess a hypothetical large population in which the effect of the induced change has stabilised the herd structure; it is the so called steady-state. Different outputs are derived from herd structure at equilibrium and these are relevant for systems evaluations or comparisons.

Although, the most common optimisation technique in agriculture is linear programming, no such model has been proposed up to now to represent sow herd management. Instead, there are examples of them in cattle and dairy production as Jalving (1992) remarked. Something different occurs with optimal control models. For instance, Chavas et al. (1985) presented such a model representing continuous biological growth of pigs to emphasise dynamic aspects of pig production against static approaches, or Burt (1993) who used the same methodology to deal with the feeding and marketing problem, but neither of them were aiming for sow herd management. Again, the discrete event nature of the reproduction process of sows makes discrete time models preferred over the rest. Nevertheless, the discretisation process can result in huge state spaces that lead to the dimensionality problem. That problem, sometimes unsolvable, has the benefit of both computational power and mathematical improvements in the way that the size of solvable models is presently larger. For instance, Kristensen (1988, 1991) proposed a methodology based on hierarchical Markov processes that has been applied successfully to solve very large examples containing millions of states (Houben et al., 1994; Verstegen et al. 1998).

2.2.4. Bridging the gap between simulation and optimisation

Optimisation and simulation methodologies constitute a broad classification of mathematical models. There are mathematical formulations that can be adapted to both purposes: optimise and simulate.

Markov models falls into this category. Usual Markov decision processes are understood as optimisation models. But when fixing a stationary policy the system therefore the resulting model is a Markov chain. In this case, assuming the transition matrix irreducible and aperiodic, to this matrix there corresponds a unique stationary distribution. Thus, the Markov chain approach takes into account the probabilistic nature of herd dynamics and both stochastic and deterministic simulations can be performed. The last is the simulation most broadly used due to its simplicity, it requires less computing time and only expectations derived from the stationary distribution are considered. Comparison of the results of herds at steady state is a good method for the evaluation of management strategies (Jalvingh et al., 1992, Plà et al., 1998). However, stochastic simulation it is also possible if individual animals are simulated under the same modelling approach. In that case the distribution of expected outcomes, mean and variance, can be estimated and also transient situations dealt.

3. SOW HERD MODELS

3.1 Selected models.

Fourteen papers related to corresponding sow herd models were considered, among them simulation was the methodology most often used to represent sow herds (ten vs. four). These models shared their interest in mimic a sow herd taken individual sow behaviour as reference, but not all of them were aimed for the same purpose. They were reviewed to illustrate different mathematical approaches to sow farms. Most of them were able to determine the effect of changes in reproduction or replacement, others considered the effect of changes in feeding and only one also considered genetic aspects. Different characteristics of them are summarised in Table 1.

One criterion of classification is the aim for which sow herd models were built. Thus we find that most of them were conceived for research purpose and their only objective was to represent farm dynamics in a suitable way. Only models presented by Jalving et al. (1992a) and Plà et al (1998) were aimed explicitly to be used on field conditions. They introduced the possible use of specific farm data to run the model, but only Plà et al. (1998, 2003) did it with real farm data. Later, Kristensen and Søllested (2004a) also supported the same idea that herd specific parameters are essential to support on decision tasks at individual farm level.

<<<<Insert Table 1.

The optimization models represented herd dynamics by transitions between different (reproductive) states, so they were all discrete in time. One difference among them concerning time representation was the temporary pattern of such transitions. Huirne et al. (1993) made use of weekly transitions which were a reasonable election motivated by the usual scheduling of farm activities by weeks, and with analytical advantages related to constant time transition matrixes. However, this pattern introduced some imprecision to force all (reproductive) states to be weekly-based. Dijkhuizen et al. (1986) considered transitions by parities while Plà et al. (1998) and Kristensen and Søllestad (2004a,b) considered natural intervals between transitions.

Huirne (1990) and Dijkhuizen et al. (1986) defined corresponding models as Dynamic Programming models characterised by a functional expression based on the herd dynamics that is maximised. Plà et al. (1998) and Kristensen and Søllestad (2004a) considered the Markov decision process embedded in a semi-Markov decision model to solve original problem, hence they obtained savings in calculation and a more natural state representation. A methodological contribution originally developed by Kristensen

(1988,1991) that exploited the structure of the transition matrix was applied in Kristensen and Søllested (2004b). They presented a hierarchic model based on the partition of the transition matrix in different sub-processes (i.e. sub-models). The advantage was the structure of the problem besides an improvement in the handling of large models. All of the authors considered time-homogeneous transition probabilities, rewards and deterministic management policies. In this way they assured the ergodicity of the stochastic process and its convergence to a steady-state distribution although it was not explicitly mentioned. Therefore, the optimisation process was related with this steady-state distribution, and the common optimisation criterion was the expected average reward per unit of time. All the authors solved the optimisation problem by an exact algorithm, and only Huirne et al. (1993) did it approximately by successive iterations.

The simulation models represented sows in the herd according a pre-stated management policy. In order to deal with discrete events like conception, sex of offspring and death, a deterministic model had to use classes of animals as the simulation unit (Tess et al., 1983a; Allen and Stewart, 1983; Jalvingh et al., 1992a; Plà et al., 2003). Thus, Tess et al. (1983a) and Allen and Stewart (1983) modelled and joined mathematically several subsystems with more or less simple links. Later on, the evolution of computational power allowed the formulation of more complex simulation models (e.g. Pettigrew et al., 1986; Singh, 1986; Pomar et al. 1991a). Sows were simulated sequentially, assuming independency among animals, only Singh (1986a) considered a synchronised simulation of the herd, and thus he was able to represent a batch management. Jalvingh et al. (1992a) considered Markov chain models to simulate herd dynamics as did also Plà et al. (1998, 2003) so they did not simulate sows individually, they were concerned in steady state herd distribution. De Roo (1987) and Jalvingh et al. (1992a) simulated the system week by week while Allen and Stewart (1983) built an event driven model. Remaining models considered a day as a time unit. Only Allen and Stewart (1983) and Singh (1986a) accounted for production facilities. On the other hand, Tess et al. (1983a) and Pomar et al. (1991a) accounted for growth process and nutrition requirements in more detail, and Tess et al. (1983a) and De Roo (1987) were concerned with genetic traits and breeding selection.

3.2 Input Parameters

Input parameters of the models depended on which kind of model we referred to, normally optimisation models had a more compact formulation than simulation models. To simulation models input parameters accustomed to be larger because the aim of these models was more general and flexible.

3.2.1. Input parameters in optimisation models

The optimisation models (Dijkhuizen et al., 1986; Huirne et al. 1993; Kristensen and Søllestad, 2004a; Plà et al. 1998) were based on sow herd dynamics by means of a partition in states of the sow lifespan as it is represented in figure 1. The more general partition was proposed by Dijkhuizen et al., (1986) who considered parity-specific parameters (probability of survival, discount rate, marginal profit per parity, length, maximum number of parities allowed, deviation of typical parity-specific litter size). Parameters considered by remaining optimisation models (Huirne et al., 1993; Plà et al., 1998 and Kristensen and Søllestad, 2004a) were in general rather similar. These parameters could be grouped in stage and state variables, economic inputs and transition probabilities. Main differences arose in the final number of states and the methods employed in parameter estimations. State variables accounted for gestation, lactation, interval weaning to first mating and interval between matings. Final number of states differed mainly due to different time pattern and litter size determination, only Plà et al. (1998) and Kristensen and Søllested (2004a) took directly into account specific-state time interval (e.g. lactation length, gestation period, etc.). More states were added to better represent the variability of production and changes in production level. In this sense, Huirne et al., (1993) and Kristensen and Søllested (2004a) considered repeatability of litter size. Most of the data used to study model behaviour was extracted from literature and less from real farms. Plà et al. (1998) and Kristensen and Søllested (2004a) presented specific-farm parameters estimated from real farm data, but using different methods (e.g. daily feed intake, litter size and transition probabilities). Dijkhuizen et al. (1986) and Huirne et al. (1993) extracted parameters values from literature or considered standard values just to illustrate model operation. In general, authors considered average parameters (e.g. gestation length, duration of lactation, oestrus interval, etc), without taking into account their specific variability.

3.2.2. Input parameters in simulation models

Simulation models included random parameters characterised by a specific distribution and not a constant value. Biological production parameter were quite similar to all models and included conception rate, number of live pigs born/litter, mortality rates at different stages, length of gestation, weaning to first oestrus interval, oestrus cycle length and growth rate per state. The way these parameters were taken into account and valued depended on the model structure, design and objective. Marsh (1986) and Singh (1986a) considered empirical distributions. For example, Singh (1986a) considered empirical distributions of Hawaii's sow farms to generate values for litter size, mortality rates and weaning to first oestrus interval, but also random distributions for other parameters e.g.

gestation and oestrus cycle length. In general, distributions used for random generation of input parameters were a normal univariate for continuous variables or a real uniform in case of transitions between states. However, several authors used other distributions to represent weaning to oestrus interval (e.g. log-normal by Pettigrew et al. (1986) and exponential by de Roo (1986)). Allen and Stewart (1983) applied normal distribution to generate the age at puberty, weight at puberty, oestrus cycle, gestation period and litter size. Real uniform was often the basis to generate different distributions when individual behaviour is represented (De Roo, 1986; Marsh, 1986; Singh, 1986a; Pettigrew et al., 1987; Pomar et al., 1991a), if not the rate was directly applied to the herd (Tess et al., 1983a; Allen and Stewart, 1983; Jalvingh et al., 1992a; Plà et al, 1998, 2003). For instance, that was the case when representing events as conception success and unforeseen casualties. Infertility or reproduction problems and injuries were the most usual culling reasons. For example, Allen and Stewart (1986) considered culling based on parity limit and death, whereas other authors were more explicative detailing infertility and additional reasons for culling (Singh, 1986a; Pettigrew et al., 1986; Pomar et al., 1991a).

Tess et al. (1983a) and Pomar et al. (1991a) based respective models upon growth process and feeding requirements, so they approached the system under a nutritionist point of view. Tess et al. (1983a) did it in a deterministic way whereas Pomar et al. (1991a) built a stochastic model. Therefore, Pomar et al. (1991a) accounted for interactions between nutrition and reproduction parameters in detail, but in general feeding requirements were largely simplified in remaining models. For example, Kristensen et al. (2004a) proposed a multiple regression model found in the literature to calculate the daily feed intake for the lactation period; Allen and Stewart (1983) considered daily feed intake of pigs in a nursery by age at weaning and chronological age like most of the authors, who just considered daily feed intake by stage (Singh, 1986a; Jalvingh et al., 1992a; Plà et al, 1998, 2003).

Pomar et al. (1991a) included a more precise description of ovulation and growth processes by a set of equations and took some parameters from previous simulation models as other authors did (Tess et al., 1983a; Allen and Stewart, 1983; Singh, 1986a; Pettigrew et al. 1987). However, they did not represent the availability of facilities that were considered by several authors (Allen and Stewart, 1983; De Roo, 1986; Singh, 1986a; Pettigrew et al. 1987). Allen and Stewart (1983) accounted for floor requirements and established a limit while Pettigrew and al. (1987) fixed a maximum number of farrowings per week as reference for room needs. De Roo (1986) and Singh (1986a) considered available places physically distributed among different buildings: breeding, gestation, farrowing, nursery and growing finishing. De Roo (1986) was the only who considered selection indices for sows and boars, besides other parity-dependent parameters.

Finally we can remark that not all of the simulation models included economic inputs as optimisation models did (e.g. De Roo, 1986; Allen and Stewart, 1983; Pomar et al.,1991a).

3.3 Outputs of the models

Outputs of the models were related with their purpose. In the simulation models there were more outputs than in the optimisation models. The optimisation models were aimed to be solved for finding an optimum (a maximum or a minimum). For instance, Kristensen and Søllested (2004b) found the optimal replacement policy for sows, like Dijkhuizen et al. (1986), Huirne et al. (1993) and Plà et al. (1998). Kristensen and Søllested (2004b) provided optimal replacement policy with associated mating strategy according to quality of sows and a summary of technical and economical results. After that, depending on the author, an analysis of sensitivity or post-optimum is performed. Thus, Dijkhuizen at al. (1986) offered technical indexes and a sensitivity analysis of several variables while Huirne et al. (1993) just calculated some performance indexes. As curiosity, only Huirne et al. (1993) reported CPU time for the optimisation process as output.

With respect to the simulation models, there was a wide variety of outputs depending largely on their construction. Then Marsh (1986) presented a lot of outputs classified in seven categories: Population, Performance indices, Reproductive performance, Monthly graphics, Cash flow analysis, Income statement and Livestock valuation. They were the same categories he used in a previous dairy model and inspired by commercial information systems. Singh (1986a), Jalvingh et al. (1992a) and Plà et al. (2003) presented different outputs related to herd dynamics. More specifically, Singh (1986a) calculated statistics about herd dynamics. In addition to different prices and costs he computed annual incomes, costs and rates of return for economic analysis. Similarly, Jalvingh et al. (1992a) calculated technical and economic variables derived from the distribution of sows over states at equilibrium. The most important were the value of piglets and the slaughter value of culled sows, costs of replaced gilts and the number of litters per sow per year and the percent of reinseminations. Plà et al. (2003) calculated differently and individually for each farm analysed technical and economic variables, but also derived from the distribution of sows over states at equilibrium. In addition, they provided different graphics related to sow distribution over states. Tess et al. (1983a) and Pomar et al. (1991a) considered animal growth in their models; therefore they showed plots of body weight of sows. Tess at al. (1983a) added growth curves, performance indexes and some rates of biological efficiency while Pomar et al. (1991a) appended statistics describing flow of animals between stages of life cycle in the herd, average sow age per day and simulated number of animals per day. Allen and Stewart (1983), Pettigrew et al. (1986) and de Roo (1987) were more concrete in calculating outputs. Thus, Allen and Stewart (1983) calculated the means of some production characters: litter size at birth, pigs born/sow/year, pigs weaned/sow/year, conception rate and Kg of pig sold per Kg of feed. Pettigrew et al. (1986) calculated sows days/pig, Pigs/sow/year, pigs/litter and litters/sow by year of simulation. Finally, de Roo (1987) calculated number of sows, farrowing index, number of inseminations, litter size at birth, litter size at weaning, statistics of culling reasons, breeding boars, imbreeding index and graphics of the effect of selection on fat, lean, growth (g/day) and feed intake.

3.4 Validation of the models

Not all of the reviewed models were validated. For example, the optimisation models were not validated, they were equivalent to deterministic models dealing with well-defined problems in the sense that they only considered mean values. The optimisation models were mainly interested in showing mathematical methodologies to solve specific problems. For instance, Kristensen and Søllestad (2004a,b) presented a new approach to sow herd modelling, hierarchical Markov decision models, based on a refinement of standard Markov decision processes in order to show its benefits. Validation in these papers was not their purpose. Instead a formal validation, authors such as Dijkhuizen et al. (1986) and Huirne et al. (1993) determined the effect of changing conditions in some major parameters, just to gain insight into the model behaviour.

Alternatively, several validation methods were used in simulation models. Authors presenting simulation models agreed that it is difficult to achieve a full validation because neither all parameters were known in practice nor suitable data for validation were available. An alternative used by several authors was to describe precisely the model without any other test to validate it (Singh, 1986a; de Roo, 1987). In some cases, the common strategy was to perform a verification based on a detailed description of the model and a check for the correct running of the model at several points in the life cycle including the final summation of inputs and outputs. As verification Allen and Stewart (1983) compared simulated results with average results reported in the literature. For partial validation, Tess et al. (1983a) and Pomar et al. (1991a) evaluated different outputs as lactation weight pattern, final body composition, litter weight at birth and at weaning, feed/gain ratios and milk production, while Allen and Stewart (1983) compared pig weaning weights (at birth and at 18 Kg) with those referred in the literature. Marsh (1986), Jalvingh et al. (1992a) and Plà et al. (2003) presented a model behaviour study based on sensitivity analysis, afterwards they compared general results with results obtained from a management information system. No statistical evaluation was presented in previous papers, only Marsh (1986) and Plà et al. (2003) did it. Marsh (1986) argued that his simulation model was based on the reproductive cycle of the sows and therefore the focus of the validation should be the reproductive events as predicted by the model. He used a non-parametric test, the Kolmogorov-Smirnov test, to test whether the observed and the simulated samples of farrowing to first oestrus interval derived from the same distribution. On the other hand, Plà et al. (2003) considered the sow herd distribution over states calculated by the model and the actual distribution observed, they used a non-parametric test, the Chi-square test, to test whether both distributions were derived from the same.

3.5 Implementation and integration opportunities

Usually, sow herd management models were programmed by the researchers themselves at least in a first stage. Most of the models were intended for research or educational purpose and only a few of them expressed their aim to be used on-farm (Dijkhuizen et al., 1986; Marsh, 1986; Jalving et al., 1992a; Plà et al. 1998). These facts may explain why user interfaces were not well enough elaborated for farmers or advisers. Procedural or object oriented languages were the most common programming languages used in software implementation, for example Marsh (1986) programmed his model in ANSI C, Huirne et al. (1993) and Jalvingh et al. (1992a) used Pascal, Plà et al. (1998) Extend™, based on C and Kristensen and Søllested (2004a) used java. Instead, Allen and Stewart (1983) and Pomar et al. (1991a) implemented the simulation models using specialised programming languages for simulation like SLAM II (Simulation Language for Alternative Modelling) or Singh (1986a) who employed GPSS (General Purpose System Simulator). The rest of papers did not mention how the models were implemented.

The on-farm use of such models was strongly related to their integration in existing information systems as modules. For instance, PORKchop (Dijkhuizen et al., 1986) pointed to possible transfer of relevant data from PigCHAMP (Stein et al., 1983) and VAMPP (Buurman et al., 1986). PigORACLE (Marsh, 1986) was built as a module of PigCHAMP. TACTSys was a management information system for tactical decision support integrating different models (Jalvingh et al., 1992a; Kamp, 1999). BD-Porc system (2000) is a management information system that contains the official databank of Spanish pig production and the model of Plà et al. (1998, 2003) were intended to be included inside as a module, although it has not yet been done. In general, despite the development of computerised herd models, the use of them as stand-alone applications is not completely successful to date (Kamp, 1999).

3.6 Risk management

Risk refers to uncertainty as consequence of farmer actions due to the unpredictable things such as prices and biological responses to different farming practices. To obtain statistically significant results from a stochastic model, as simulation models are, it is necessary to generate a large number of independent observations on the random variable of interest. Therefore, Singh (1986a) run the model 10 consecutive years taking a sample per year and used the Student *t* distribution to test the average income and to obtain the 95% confidence interval of the yearly average income. Pettigrew et al. (1986) replicated each alternative three times and compared them by ANOVA in a completely random design.

Optimisation models ignored uncertainty associated to their results, although it was considered implicitly for most of the parameters of the model. Therefore, the results performed by optimisation models were directed at risk neutral decision makers due to the fact that they were just expectations.

3.7 Further applications and related works

When the description of the models to show the power or full capabilities of them were not enough, several authors included brief examples of use. For instance, Allen and Stewart (1983) compared alternative management practices of 3 and 6 week lactations. Pettigrew et al. (1986) simulated several alternatives to compare them (decreased mortality, more uniform age at puberty, split weaning, increased litter size and increased prolificacy). Dijkhuizen et al. (1986), Huirne et al. (1990) and Jalvingh et al. (1992a) did an analysis of sensibility for main productive variables in order to check their impact on model performances.

In general, most of the reviewed models were used in later works that provide more precise examples of potential applications. For example, to study the occupancy of facilities based on the model of Singh (1986a) were published (Singh, 1986b). Similarly Lippus et al. (1996) and Plà et al. (2004a) applied the model of Jalvingh et al. (1992a) and Plà et al. (2003) respectively to study the same problem. Also it raised examples of applications in field conditions, for example Alsop et al. (1994) used the model of Jalvingh et al. (1992a) with empirical data and Plà et al. (2004b) built a decision support system for on-farm use. The model of Huirne et al. (1993) was also used in different works to evaluate replacement alternatives (Huirne, 1990), and that of Dijkhuizen et al. (1986) was used to analyse economic reasons in replacement (Dijkhuizen et al., 1989). Houben et al. (1990) modified the model of de Roo (1987) to calculate litters/sow/year, pigs weaned/sow/year, profit/sow and profit/herd. Later on, they applied their model to compare the outputs of different insemination and replacement policies in order to find the more suitable combination of them. Similarly, Jalvingh et al., (1992b) made an economic comparison of management strategies on reproduction and replacement in sow herds using the model proposed earlier by themselves (Jalvingh et al., 1992a). Sometimes, reviewed models were included as a part of a bigger system described sometimes elsewhere (Tess et al. 1983a, 1983b, 1983c, Pomar et al. 1991a, 1991b, 1991c and Kristensen and Søllested 2004a, 2004b).

4. DISCUSSION

The reviewed sow herd models were focused on reproduction as main process determining herd production. Although Jalvingh (1992, 1993) argued that an enormous variation in structure is observed in this kind of models many similarities in the modelling approach at mathematical level have been found. For instance, the main common trait was the use of discrete models better than continuous ones attending the discrete nature of the reproduction process. Moreover, main decisional aspects involved replacement, lactation and breeding policies or a combination of them. In addition, variability in sow performance during sow lifespan and herd composition induced the formulation of dynamic models in all the cases.

There was a general agreement with respect to the variables to take into account for describing the herd system but noticeable differences were encountered in the way, detail and emphasis used in their description. For instance, there was a stressed coverage of variables describing the reproduction process and a lesser one of those related with feeding, growth, economics, facilities or genetics. Then, Glen (1987) had considered this fact a major weakness for practical use of current livestock models since the economic efficiency of livestock production is misrepresented. Nevertheless, known factors involved in herd management can neither represent all observed variability nor be replaced by hypotheses or guesses as Pomar et al. (1991a) had reckoned. Therefore, simplifications and assumptions have to be compatible with the aim of the model.

Most animal traits were considered independent and identically distributed that allowed simplifications to the modelling process, for example considering animals independent and aggregating them in states. As consequence interactions between animals were difficult to be represented. Complexities of this kind have been dealt more easily in simulation than optimisation models, for instance modelling batch management and housing facilities (Singh, 1986a). However, the inclusion of excessive randomness in models for on-farm decision support is a possible source of confusion and reduction in the acceptance to the end-user (Upton, 1993).

There were effects not easy to model as for example seasonal effects on fertility that Marsh (1985) and Singh (1986a) tried to capture through empirical distributions. Farm-specific input parameters are essential to represent individual farm behaviour. As shown, only Plà et al. (1998, 2003) and Kristensen and Søllested (2004a, 2004b) used farm-specific input parameters whilst most of the models assigned values calculated from general databases or extracted from literature. The last is good to verify the model and for academic and research purposes, but not so for giving advice at herd level since a specific farm is not represented. On the other hand, input parameters were considered time homogeneous in all reviewed models, but time to time new data are collected in farms and therefore input updates or a revision of hypotheses would seem reasonable as Toft (1998) pointed out. In this sense Kristensen and Søllested (2004a, 2004b) used a dynamic linear model (DLM) to update litter size expectation depending on previous observations and Plà et al. (2003) proposed the analysis of actual herd structure over time to assess the stability of the system.

The simulation and optimisation models concentrated on steady-state studies (long run or infinite time horizon respectively) making unnecessary to consider initial condition of the farm. This is very useful to compare management strategies at equilibrium as Jalvingh (1992) noticed. However, the productive path to follow a farm from actual management strategy to the new one at equilibrium prescribed by any of the models is not depicted or valued. The convergence from original situation to the new steady-state may have important practical implications to be taken into account. This reveals a lack of transient models or analysis linking the theoretic-academic and the real-pragmatic world.

Concerning outputs, existing models only provide mean values without corresponding confidence interval calculation or variability measurement, even the simulation models, what makes difficult statistical comparison between alternatives or a complementary risk analysis. On the other hand, although studied optimisation models intended to capture the dynamic-stochastic nature of the system by including probabilities, their operational formulation and resolution was based on equivalent static-deterministic models which actually provided the solution. White (1988) had already pointed out the need of different criteria to reflect variability risk features to fully capture the various aspects of a decision maker rather than the usual average criteria examined in the literature on Markov decision processes. In this sense, the variance of cumulative rewards can be an alternative deployed by Sladky (2005). Other authors (e.g. Pannell et al. 2000) argued for using multicriteria methods instead of the dominating monocriterion approaches in this kind of models.

The validation of the models is essential to gain credibility and acceptance for practical use. Several authors had argued that they lacked suitable data to perform the validation, but Kleijnen (1995) proposed different methodologies of validation, even in cases where data is missing, emphasising statistical techniques that yield reproducible, objective, quantitative data about the quality of simulation models. For instance, herd structure was relevant in all models and central to calculate outputs in many of them as Jalvingh et al. (1992a) recognised. Moreover, it is one of the recurrent topics in practical herd management, the so-called ideal herd structure in close relation with the culling rate. Therefore, Plà et al. (1998) proposed the herd distribution at equilibrium as a way to validate this kind of models. Furthermore, concerning Markov simulation models, the average result of expected outcomes in stochastic simulation has to converge to that in deterministic simulation; this fact can be used to verify some instances of complex simulation models as Plà (2005) did.

In the eighties, simplifications required for an adequate solving process by computers prevented the practical use of reviewed models on farm. Debertin et al. (1981) suggested that whenever models run interactively or results are quickly available, the use of mathematical models can have a significant impact on farmer's decision making behaviour. Methodological and computational advances made the number of potential applications and the implementation of decision support systems (DSS) increase (cf section 3.7). This fact encouraged the integration of many of such models in existing management information systems, but without much success because if their aim was to be used in field conditions instead of the real system this has not been yet achieved as Kamp (1999) already noticed. Reasons for that were the skills required to interpret results of these systems and the involvement of end-users (e.g. farmers, swine specialists or extension service advisers) in the different stages of development. In this way Panell et al. (2000) argued that actual decision models were not fitted to farmers' demand who are more interested in getting the big decisions right and making correctly major tactical adjustments.

The interface of practical applications for use at farm level based on complex models should be simple, comprehensible and capable of preventing mistakes or strange outcomes. A solution to satisfy these requirements would be the addition of expert systems as various authors proposed (Huirne, 1990a,1990b), though this would lead to program sophisticated user interfaces lacking in actual applications. Nevertheless, this trend is observed to change or being complemented by the irruption of internet, e-business and on-line services. For instance, at present many management information systems are starting to provide support through Internet. However, if the counterbalance is short the use of these technologies for supporting decision processes can be frustrated.

Finally, the outlook for the swine industry is changing because producers are vertically integrated in bigger companies, cooperatives or associations and this means that farmers contract their production under several conditions. So, in many cases this contract is in truth a hire of facilities and farmer labour. Moreover, each company usually has their own service of advisers who act as real pig managers (their advises are implemented by farmers, if not farmers are penalised according to the contract agreed). Thus, goals and targets are fixed from companies and real independent farmers managing one sow farm are expected to become very rare. At the same time, devices for automatic data acquisition are increasing and the volume of data to be processed is becoming important as well as the need of their integration in existing systems. In this context, decision problems even being the same are involving more than one farm and a huge amount of data. They may bring new modelling developments to cope with this new practical situation. Hence, it is expected in the near future new contributions will appear in literature in this direction.

5. CONCLUSIONS

There is no single correct way to build a sow herd model. It depends on their purpose but simplifications and assumptions have to be compatible with the aim of the model. Many of such models have been developed successfully as research tools and teaching aids.

They might be used to explore assumptions and hypotheses being good for learning but not so for advising. Much has been done on the methodological domain and very complex models have been proven to be solvable, however, a long way remains to make before sow herd models can be used efficiently in support decision tasks. Reasonable amount of data from real farms are now available for validation and also for inferring specific parameters representing individual farm behaviour. It has only been quite recently that specific farm parameters have been introduced as well as the use of real farm data for validation. Nevertheless, validation of this kind of models is still a problem. It is necessary that they be reliable tools to gain credibility and assure their widespread use in field conditions.

A need of transient models or short time horizon decision models adapted to the changing environment of pig production is detected. Proposals made up to now considered steady-state situations which are not present as much as desired in real farms. Something similar is observed with the assumption of time-homogeneity of parameters where in a likely changing environment a regular update of estimations should be required.

On the other hand, the revision of optimality criteria is also advisable since the use of expected total return per unit of time may be quite insufficient to characterise the problem from the point of view of the farm manager. In this sense, the inclusion of variability-risk features of the problem or other multicriteria approaches seems relevant for future proposals.

The integration of these models in existing management information systems and their use by farmers has not been successful and the interface has also contributed to it. However, it is expected an important impact of internet on the development and use of these models for on farm decision support if they are capable of providing relevant answers for the users.

Finally, the new structure of the sector, with bigger companies and or associations and lesser independent farmers, makes new decision problems appear and move the centre of decision out of the farm. Therefore, new models taking into account a pool of farms instead of an isolate independent farm will have to be developed in answer to current concerns.

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Table 1. Main characteristics of sow herd models reviewed

Authors	Year	Aspects	Model	Title
Allen and Stewart	1983	R	S	A simulation model for a swine breeding unit producing feeder pigs
Tess et al.	1983	R,F,E	S	Simulation Of Genetic Changes In Life Cycle Efficiency of Pork Production I. A Bioeconomic Model
Dijkhuizen et al.	1986	RP,E	OP	Economic optimization of culling strategies in swine breeding herds, using the "PORKCHOP computer program"
Marsh	1986	R,E	S	Economic decision making on health and management in livestock herds: examining complex problems through computer simulation
Pettigrew et al.	1986	R,E	S	Integration of factors affecting sow efficiency: a modeling approach
Signh	1986	R,E	S	Simulation of swine herd population dynamics
de Roo	1987	R,G,F	S	A stochastic model to study breeding schemes in a small pig population.
Pomar et al.	1991	R,F	S	Computer simulation model of swine production systems: III. A dynamic herd simulation model including reproduction.

Jalving et al.	1992	R,RP,E	S	Dynamic probabilistic modelling of reproduction and replacement management in sow herds. General aspects and model description
Huirne et al.	1993	R,RP,E	OP	An Application of Stochastic Dynamic Programming To Support sow replacement decisions
Plà et al.	1998	R,RP,E	OP-S	A sow model for decision aid at farm level
Plà et al.	2003	R, E	S	A Markov decision sow model representing the productive lifespan of herd sows
Kristensen and Søllestad	2004a	R,RP,E	OP	A sow replacement model using Bayesian updating in a three-level hierarchic Markov process I. Biological model.
	2004b			A sow replacement model using Bayesian updating in a three-level hierarchic Markov process II. Optimization model.

R: reproduction, RP: replacement, E: economics, F: feeding, G: genetics

S: simulation, O: optimisation

Figure 1. Principal events and cyclic pattern in sow reproduction