Agricultural Systems 165 (2018) 221–229

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

Global sensitivity analysis of a pig fattening unit model simulating technico-economic performance and environmental impacts

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ARTICLE INFO

Keywords:
Individual-based model
Global sensitivity analysis
Scaled elementary effect
Livestock farming system
Multiple outputs
Life cycle assessment

ABSTRACT

Livestock farming system (LFS) models are used to produce key technical or economic outputs. Current models simulate multicriteria performance of LFS, i.e. technical, economic and environmental outputs. Therefore, conducting sensitivity analysis (SA) of these models is increasingly challenging. We developed a pig fattening unit model which is a stochastic, discrete-event mechanistic model with a one-day time step. An individual-based model is used to represent the pigs. Our objective was to perform a global SA of this model while accounting for effects of parameters on all outputs. Due to the model's long computational time, we first performed screening SA using the Morris method to identify and exclude non-influential parameters, and then performed variance-based SA of the influential parameters using metamodels. The most influential parameters were mainly pig characteristics and the disinfection period. This study provides a generic SA sequence adapted for models with a high computational cost and multiple outputs.

1. Introduction

Livestock farming system (LFS) models are useful to study and understand the mechanisms by which these systems respond to changes in their environment and/or management (Pla, 2007; Gouttenoire et al., 2011; Ozkan et al., 2016). These models usually focus on one or a few issues (e.g. disease spread (Lurette et al., 2008), reproductive performance (Martel et al., 2009), emissions to the environment (Rigolot et al., 2010)). More recent studies developing LFS models have addressed many more issues; consequently, these models have provided multiple outputs related to the multicriteria evaluation of sustainability (Chardon et al., 2012; Ozkan et al., 2016). This shift to multiple outputs raises several issues during model calibration, identification of key parameters, and evaluation of the accuracy of predictions. These steps of the modelling process are essential to ensure that model behaviour is consistent with expert knowledge, that the model is free of coding errors, and that its use is consistent with its range of validity. Among these steps, sensitivity analyses (SA) are commonly used for these complex models to identify the parameters that influence model outputs the most (Iooss and Lemaître, 2015). Two types of SA are used in the literature: local and global. Currently, local and screening SA are the most common methods used to study the behaviour of LFS models (Rigolot et al., 2010; Reckmann et al., 2013; Groen et al., 2016; Kebreab et al., 2016; Pearson et al., 2016). Local SA consists of varying one parameter at a time in a given range (often ± 10% around its mean). This approach, which is fast and simple, does not require many simulations. However, it does not assess the true sensitivity of model outputs to parameters nor consider potential interactions among parameters. In contrast, global SA consists of changing all tested parameters over their entire intervals of variation, which provides an appropriate evaluation of model sensitivity and interactions among parameters. However, it requires more simulations and raises issues about the amount of time the latter will require. Several studies have applied global SA and suggested that both screening and variance-based SA steps must be performed (Saltelli and Annoni, 2010; Schouten et al., 2014), to select with the screening SA the most contributing parameters which contribution is then quantified with the variance-based SA. To our knowledge, however, they have not combined the existing analyses into a general strategy for global SA of models with multiple outputs and a relatively long computational time (> 1 min). This generates the following issues: how to minimise the amount of time required for SA simulations, and how to perform screening and variance-based SA for models with multiple outputs.

In a previous study (Cadero et al., 2018), we developed a simulation model of a pig fattening unit which predicts multiple performance indicators in three dimensions: technical, economic and environmental

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https://doi.org/10.1016/j.agsy.2018.06.016
Received 29 August 2017; Received in revised form 13 April 2018; Accepted 25 June 2018
Available online 06 July 2018
0308-521X/

(the last one via Life Cycle Assessment (LCA)). The model accounts for interactions among farm management, pig biological characteristics and farm infrastructure. The model uses an individual-based approach to simulate 14,000 fattening pigs; thus, each simulation of a two-year production period takes approximately 5 min. Computational cost is an important issue to consider when performing global SA, which require hundreds, if not thousands, of simulations. For models with a long computational time, studies usually recommend using local or screening SA, and excluding non-influential parameters for variance-based SA (Ginot et al., 2006; Imron et al., 2012), or building metamodels first and then performing variance-based SA (dos Santos and dos Santos, 2009; Marrel et al., 2011; Iooss and Lemaître, 2015).

The present study aimed to (i) perform an adequate global SA of our model and use the SA results to help transform the model into a decision support tool and (ii) develop a chain of analyses for SA of LFS models with multiple outputs and a long computational time.

2. Material and methods

2.1. Description of the fattening unit model

The fattening unit model is a discrete-event mechanistic model which has stochastic biological traits (pig intake, growth potential and risk of mortality) and a one-day time step (Cadero et al., 2017). The pig fattening system consists of three entities: the pig herd, farm management and farm infrastructure. The pig herd is divided into successive batches of pigs of the same age which are reared in the same room from the beginning of the fattening period until shipping to the slaughterhouse. Pigs are represented using an individual-based model adapted from the InraPorc model (van Milgen et al., 2008). The InraPorc model simulates feed intake, body protein and body lipid depositions, and the resulting growth and nutrient excretion of each pig. Each pig is attributed a profile which includes an initial weight and parameters describing its feed intake and growth potential, set to generate the appropriate variability within a pig herd in terms of mean growth and feed intake performance according to Vautier et al. (2013). The management of the farm is represented through practices and a calendar of events containing tasks to perform. Each day, information from the herd and the calendar of events are sent to the farmer. The calendar is updated by adding or removing events according to this information, and the events corresponding to the current day are processed. The practices include batch management, allocation of pigs to pens, feeding practices and slaughter shipping practices. Farm infrastructure is represented by a number of fattening rooms, each with a number of pens of a given size, which are provided as input parameters to the model. A buffer room can be used at the end of the fattening period to extend the fattening period of the lightest pigs which have not reached the minimum slaughter weight without economic penalties. Once the last pigs in a batch are moved to the slaughterhouse or in the buffer room, a fattening room is considered empty after a disinfection period. The model calculates technical, economic and environmental results for each fattening pig and globally for the unit. Environmental impacts of each slaughtered pig are estimated using LCA, taking into account impacts from the extraction of raw materials to the farm gate. Environmental impacts of producing piglets in farrowing and post-weaning units are calculated according to average references of animal performance (IFIP, 2015) and feed composition. Environmental impacts of feed ingredients came from the ECOALIM dataset (Wilfart et al., 2016), while those of feed transport and processing came from Garcia-Launay et al. (2014). Background data (i.e. impacts of road transport, electricity, light fuel oil and natural gas used in the pig unit) came from the ecoinvent database V3.1 (Weidema et al., 2013). A system expansion approach was used to estimate impacts of manure use (Garcia-Launay et al., 2014). Processes for manure transport and spreading came from AGRIBALYSE V3.1 (Koch and Salou, 2015). We considered potential impacts of the fattening pig unit on climate change (CC, 100-year horizon, kg CO_2-eq), eutrophication potential (EU, g PO_4^{-}-eq), acidification potential (AC, g SO_2-eq), cumulative energy demand (CED, MJ) and land occupation (LO, m^2year). More detailed description of the model and the LCA performed by the model can be found in Cadero et al. (2017).

2.2. A three-step sensitivity analysis sequence

We developed and applied a global SA sequence to estimate the sensitivity of model outputs to input parameters. To address the long computational time and large numbers of parameters and outputs, we combined a screening SA method, i.e. the Morris (1991) method, construction of metamodels with the most influential parameters, and a variance-based SA method, i.e. the Sobol method (Sobol, 1993; Saltelli, 2002). Focusing on the most influential parameters with the screening SA and using metamodels decreases the computational cost time of the variance-based SA. Another challenge was to assess the influence of the parameters on multiple outputs of different dimensions (technical, economic and environmental). For this purpose, we calculated Morris indices according to Sin and Gernaey (2009) in order to obtain non-dimensional indices that can be compared between outputs. We calculated Sobol first (without interaction between parameters) and total order (including all interactions between parameters) indices with a method adapted from Lamboni et al. (2011) and Gamboa and Janon (2014) to obtain aggregated indices for each input. This provided a three-step SA sequence to assess the model (Fig. 1).

To begin the SA, we selected the parameters, outputs and scenarios for which the SA would be performed. A scenario consists of a combination of fixed values for qualitative inputs of the model (e.g. type of batch management, ad libitum or restricted distribution of feed) which are not tested in the SA.

The first step is to screen the parameters with the Morris method to identify those which are least influential for all outputs and scenarios. To obtain stable value of sensitivity indices with the variance-based SA, a high number of simulations has to be performed, sometimes up to 10,000 simulations per parameter (Faivre et al., 2013). Therefore, to limit the number of simulations and ensure stable variance-based sensitivity indices, we selected a maximum of 10 most influential parameters from the Morris SA.

The second step is to construct metamodels using the influential parameters and then to evaluate the metamodels (Wallach et al., 2014). A metamodel is a simple approximation of a complex model. It is constructed from simple mathematical functions to simulate the behaviour of the original model under specific conditions. We constructed one metamodel per output and per scenario.

The third step is to perform variance-based SA with the Sobol method using the influential parameters and metamodels. Results of this step are Sobol first- and total-order indices for all parameters analysed.

Before applying this SA sequence, we assessed effects of model stochasticity on variability in its outputs. Parameters were set at their default values, and 100 simulations were performed for each scenario. The mean coefficient of variation of the outputs was 0.4%, with a maximum of 3.4% for the gross margin (Table B.1 in supplementary material). Given the small influence of stochasticity on mean output values and the increase in computational time (×100) required for replicate stochastic simulations, we set the model's random seed to the same value for all simulations.

2.3. Selection of the parameters, outputs, and scenarios

The model contains 41 input factors, of which 14 are discrete variables describing management practices, and 12 are either set or calculated from other factors. The 15 remaining factors are continuous parameters and were tested in the SA (Table 1). Lower and upper boundaries of the parameters, used to design the SA, were set according