



Economic optimization of feeding and shipping strategies in pig-fattening using an individual-based model

M. Davoudkhani, Fabrice Mahé, Jean-Yves Dourmad, Alexandre Gohin, E. Darrigrand, Florence Garcia

► To cite this version:

M. Davoudkhani, Fabrice Mahé, Jean-Yves Dourmad, Alexandre Gohin, E. Darrigrand, et al.. Economic optimization of feeding and shipping strategies in pig-fattening using an individual-based model. *Agricultural Systems*, 2020, 184, pp.102899. 10.1016/j.agsy.2020.102899 . hal-02959080

HAL Id: hal-02959080

<https://hal.science/hal-02959080>

Submitted on 23 Aug 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

Economic optimization of feeding and shipping strategies in pig-fattening using an individual-based model

M. Davoudkhani¹, F. Mahé², J.Y. Dourmad¹, A. Gohin³, E. Darrigrand², F. Garcia-Launay¹

¹PEGASE, INRAE, Institut Agro, 35590 Saint Gilles, France

²Université de Rennes, CNRS, IRMAR - UMR 6625, F-35000 Rennes, France

³SMART LERECO, INRAE, Institut Agro, 35011 Rennes, France

Keywords: Optimization procedure, Bioeconomic simulation model, Gross margin, Evolutionary algorithm, Market price.

ABSTRACT

Economic results of pig-fattening systems vary greatly and depend mainly on prices of pork and feeds, and pig growth performance (e.g. feed efficiency, slaughter weight, lean percentage). Previous studies revealed that feeding and shipping strategies are critical factors in the economic outputs of pig production. However, they failed to consider both strategies and the variability in pig growth performance simultaneously. Consequently, we developed a new approach to improve the profitability of pig farms by estimating the best compromise among feeding costs, animal performance, and shipping constraints. We used an individual-based bioeconomic model that simulates the growth of each pig according to its biological traits (e.g. feed intake and protein deposition potential) as a function of different feeding and shipping strategies. The optimization problem is solved using an evolutionary algorithm (CMA-ES, covariance matrix adaptation evolution strategy) that manages the objective function, which is discontinuous, non-convex, nonlinear, and multimodal. Various case studies were constructed to investigate the behavior of the optimization procedure. Effects of pork price on optimal strategies were investigated using three different price scenarios: **low (1.173 €/kg), medium (1.314 €/kg), and high (1.662 €/kg) pork prices**. Optimizing only feeding strategies improved the gross margin per pig by 5.0% while optimizing shipping

strategies improved the mean gross margin per pig by 4.7%. Optimizing both feeding and shipping strategies improved the gross margin per fattened pig by 10% (2.88 €/pig, with medium pork price (1.314€/kg)) compared to the common practice on farms in France. Pork price had a limited effect on feeding decisions when optimized alone, but a strong impact on shipping decisions. Economic optimization of pig fattening inconsistently affected the environmental impacts. However, increasing pork price improved the optimized mean gross margin per pig but increased all environmental impacts. To our knowledge, this is the first tool able to optimize both feeding and shipping strategies while considering effects of variability in growth potential among a batch of pigs. These features allow consideration of the interaction effect of feeding and shipping strategies on the economic outputs of the batch, and investigation of the trade-off between production cost and technical performance. This tool should interest the pig sector since it can identify the best feeding and shipping strategies depending on the economic context. Further work should consider multiobjective optimization with both economic and environmental objectives.

1. Introduction

The world population is expected to reach 9.8 billion by 2050, an increase of 20 percent from today (FAO, 2017). Coupled with an improving standard of living in developing countries, this will increase demand for animal products by 50% (FAO, 2017). The expected growth in animal production raises many concerns about its short and long-term effects. Pork is the most consumed meat in the world. It accounts for 39% of the world's meat intake in 2015 (OECD/FAO, 2016) and its demand is increasing (+37% expected over the period 2010-2050).

Pig production contributes to various environmental impacts, like climate change, acidification, and eutrophication (McAuliffe et al., 2016). Fattening pigs contribute to 70% of total phosphorus (P) and nitrogen (N) excretions on farrow-to-finish farms (Dourmad et al., 1999), and therefore to environmental impacts of pig production. In the past decade, European market prices of pigs and raw ingredients used in pig feeds began to vary greatly. Consequently, the profitability of pig-fattening

units has remained unstable. This new volatile context likely affects the optimal feeding strategy and optimal delivery of pigs to the slaughterhouse.

The pig-fattening unit, which is the main contributor to environmental impacts of pig production, represents the majority of pig production costs (Pomar and Remus, 2019) and its profitability depends largely on market prices of pig carcasses and feed ingredients (Pourmoayed et al., 2016; AHDB, 2018). Farmers receive revenue from delivering pigs to the slaughterhouse when pigs reach a marketable weight or when the fattening room must be emptied in the “All-in All-out” management system (Plà-Aragones and Rodríguez-Sánchez, 2015). In most European countries, the revenue from each pig depends on carcass weight and carcass leanness, which are assessed by a payment grid. Carcass weight resulting in a premium or a discount (per kg of carcass weight) is achieved at a different fattening duration for each pig in the batch. This is due to variability in feed intake and potential for body protein deposition among pigs. Feeding costs depend on the price of feeds and the total consumption of each pig, which also varies among pigs and depends on the ability of the feeding strategy to meet the pigs’ nutritional requirements. In practice, for a given pig, extending the fattening duration increases both carcass weight and feeding costs but decreases carcass leanness. Depending on each pig’s potential, the feeding strategy, and the market price, extending fattening duration may decrease or increase the gross margin (Leen et al., 2018). In the meantime, extending the fattening duration increases environmental impacts. The gross margin per pig, feeding costs and environmental impacts can thus vary considerably depending on the feeding program. Therefore, interactions between feeding programs, the delivery of pigs to the slaughterhouse, and the variability in pig growth performance largely determine the profitability of the pig-fattening unit and the consequences of the production on the environment; however, they are difficult to predict. The purpose of this study was to account for these interactions when optimizing the economic output of a batch of pigs.

The scientific community has focused on the nutritional requirements of growing pigs for energy and amino acids (van Milgen et al., 2008; Van Barneveld et al., 2018). Nutritional requirements vary greatly among pigs and change over time during the fattening period. Most pigs on commercial farms

79 receive no more than two or three successive feeds in the fattening unit. Brossard et al. (2014)
80 highlighted that regardless of the number of feeding phases, the percentage of pigs that have their
81 digestible lysine requirements (i.e. the most limiting amino acid in the diet) met at the start of each
82 phase is essential for the profitability of the unit. Given the complexity of the pig-fattening unit
83 system, optimizing feeding and shipping strategies requires 1) predicting the variability in
84 performance among pigs depending on the feeding strategy and 2) predicting deliveries to the
85 slaughterhouse depending on a target weight.

86 Effects of feeding and shipping strategies on animal performance and the economic return of the pig-
87 fattening unit have received substantial attention. They have been tested extensively via experiments
88 (Conte et al., 2011; Pomar et al., 2013; Andretta et al., 2016; López-Vergé et al., 2018) and simulation
89 models (Ali et al., 2018; Cadero et al., 2018a; Peña Fernández et al., 2019). However, experiments
90 provide few insights into optimal strategies and simulation models compare scenarios that are not
91 necessarily optimal.

92 Previous studies have addressed the issue of economic optimization of pig-fattening units (Morel et
93 al., 2012; Nadal-Roig et al., 2018; Leen et al., 2018) and broilers (Gous and Berhe, 2006). Most
94 studies focused on optimizing pig deliveries to the slaughterhouse (Nadal-Roig et al., 2018; Leen et
95 al., 2018; Kristensen et al., 2012) or optimizing the nutrients in feeds (e.g., energy and digestible
96 lysine, Morel et al., 2012). Some studies also focused on feed formulation in the context of multiphase
97 feeding (Joannopoulos et al., 2015; Joannopoulos, 2018). Morel et al. (2012) used a stochastic growth
98 model that was sensitive to the feeding program to optimize feeding strategies and included the
99 variability in growth performance. To our knowledge, only Niemi (2006) addressed optimization of
100 feeding and shipping strategies. However, the model developed by Niemi (2006) was based upon an
101 average pig performance and without the variability in growth performance. This is a major
102 drawback, because there is an interaction effect of the variability in growth potential among pigs, and
103 feeding and shipping strategies on the technical and economic performance of the pig-fattening unit
104 (Cadero et al. 2018a).

105 Given this context, the main goals of the present study were to investigate 1) the effect of the
106 interactions between feeding and shipping strategies when optimizing the gross margin of a batch of
107 growing pigs, and 2) the effect of pork price on optimal feeding and shipping strategies. For that
108 purpose, we considered (for the first time) the variability in performances among pigs in an
109 optimization model of a batch of pigs. In this article, we describe the model and the optimization
110 procedure, and explore their behavior with different case studies.

111

112 **2. Materials and methods**

113 In this section, we first provide a general overview of the bioeconomic model. Next, we describe the
114 complex features that make the optimization challenging and justify our optimization approach. Then,
115 we explain how we explore the behavior of our model and the applications performed.

116 *2.1 General overview of the bioeconomic model*

117 This study couples a bioeconomic model of the pig-fattening unit adapted from Cadero et al. (2018a)
118 with an optimization procedure that considers an objective function (i.e., mean gross margin per pig),
119 to optimize feeding and shipping strategies (Figure 1). The bioeconomic model is a discrete-event
120 mechanistic model that considers farm data and biological traits such as pig feed intake, growth
121 potential, and mortality rate while addressing the stochastic nature of the pig production system. The
122 main entities in the pig-fattening system represented are the batch of pigs, farm management, and
123 farm infrastructure. Pig growth is represented using an individual-based model adapted from the
124 InraPorc model (van Milgen et al., 2008). In this model, each pig is defined by a biologic profile that
125 is used to calculate its growth and nutrient excretion depending on the feeding program. Five
126 parameters are used to describe the pig profile: initial body weight, the two parameters in the equation
127 for feed intake, average protein deposition between 70 days of age and 110 kg body weight (BW),
128 and the shape parameter of the Gompertz function that describes the precocity of protein deposition.
129 In the model, we use a database, which includes 1000 male and 1000 female pig profiles
130 (characterized by individual growth and feed intake potentials). To create a batch of pigs, by default,

131 the model selects randomly from this database the same number of males and females to generate the
132 appropriate variability within the pig herd. The model can be run either with all pigs characterized by
133 the same average pig profile or with individual pig profiles taken at random within a set of 1000 male
134 and 1000 female pig profiles (Brossard et al., 2014). These values for each pig are set according to
135 the profile of the average pig and a variance-covariance matrix of the parameters to generate the
136 appropriate variability within the pig herd (Vautier et al., 2013). Farm infrastructure consists of
137 fattening rooms, with a number of pens of a given size in each room, and possibly a buffer room to
138 extend the fattening duration of light pigs. This information is provided as input parameters of the
139 bioeconomic model. Farm management includes batch management, allocation of pigs to pens,
140 feeding practices, and shipping practices to send pigs to the slaughterhouse, as well as a calendar of
141 events containing tasks to perform.

142 In this model, feeding strategies combine a series of feeds in a feed sequence plan, a feed rationing
143 plan, and a level of application. Feeds are described by their nutrient contents and formula (i.e.
144 incorporation rates of each ingredient). The feed sequence plan describes which feed or which blend
145 of feeds is distributed in each feeding phase of the sequence, and provides rules to shift from one
146 feeding phase to the next. The feed rationing plan defines the quantity of feed distributed per pig for
147 each day of the fattening period. The feeding strategy, as defined in the model, also includes a level
148 of application of the feed sequence and feed rationing plans (batch, pen, or individual pig).

149 In the model, shipping strategies are defined by the target weight at slaughter, the maximum fattening
150 duration, and the maximum time that pigs are kept in the buffer room, when applicable. Target weight
151 at slaughter is used to determine whether a pig is ready to be sent to the slaughterhouse. Once a week,
152 the model compares the weight of each pig in the whole batch to the target weight. If any pig from
153 any pen reaches the target weight, it is selected for shipment to the slaughterhouse (individual
154 marketing). The maximum fattening duration depends on batch management and determines the date
155 that fattening rooms must be emptied. In order to clean and disinfect the room before the arrival of a
156 new batch, all pigs must be sent to the slaughterhouse or the buffer room. It means that the latest day

157 of a possible delivery of the batch to slaughterhouse corresponds to the maximum fattening duration
158 minus the duration of the cleaning period. The maximum time that pigs are kept in the buffer room
159 determines the date that the buffer room must be emptied. On most farms, light pigs are not transferred
160 to the next batch. It is even highly recommended not to do this because of the high sanitary risk of
161 contamination of the next batch. They are either delivered to the slaughterhouse or sometime
162 transferred to a buffer room, but this is not the most usual practice. Indeed, the necessity of a buffer
163 room depends on the adequation between batch management and the number of fattening rooms in a
164 given unit. In our case, we considered a maximum fattening duration of 108 days, which corresponds
165 to the usual practice in France (Cadero et al., 2018a). Therefore, we did not account for a batch with
166 a buffer room but the model has the ability to handle it. The presence or absence of a buffer room is
167 an input parameter of the model.

168 The minimum number of pigs detected ready to be sent to the slaughterhouse to schedule a shipment
169 was set to 1 because we considered that a truck is not only filled with pigs from a single batch but
170 with pigs from the whole unit. However, we only allowed a maximum of one delivery per week to
171 get a flow of deliveries consistent with what was observed in a previous study (Cadero et al., 2018c).

172 The bioeconomic model produces technical results for each pig on a daily basis and throughout the
173 fattening period. These outputs are then used to calculate the economic results and environmental
174 impacts per kg of pig live weight gain according to life cycle assessment (LCA) approach (Cadero et
175 al., 2018a). The perimeter of the environmental evaluation includes impacts from the extraction of
176 raw ingredients for crop production used for feeds, up to the farm gate. Potential impacts of the pig-
177 fattening unit on climate change, eutrophication potential, acidification potential, cumulative energy
178 demand, and land occupation were also calculated. Finally, the results for each individual pig were
179 aggregated to calculate technical, economic, and environmental results at the whole-batch level. The
180 model is described in more detail by Cadero et al. (2018a) (Figure 1).

2.2. Definition of the optimization problem

The model developed by Cadero et al. (2018a) is a simulation model, which is not able to find optimal feeding and shipping strategies in different economic contexts. Consequently, the present study developed an optimization procedure that overcomes this missing feature, maximizes the economic performance of a batch of pigs, and identifies the best feeding and shipping strategies in a given economic context.

The optimization procedure attempts to maximize the objective function, which is the mean gross margin per fattened pig by optimizing the feeding and shipping strategies:

$$Obj(X, \alpha, TW, Max_d) = \frac{1}{I} \sum_{i=1}^I \sum_{g=1}^3 GM^{ig}(X, \alpha, TW, Max_d). \quad (1)$$

In this optimization problem, we consider a feeding sequence of p phases that uses two feeds, A and B which are mixed in variable proportions at each phase. In this context, feed A has high nutrient density to meet requirements at the start of the fattening period, while feed B has low nutrient density. The shipping strategy focuses on optimizing the decision to send pigs to the slaughterhouse up to the emptying of the fattening room (the use of a buffer room is not considered). The decision variables (Table 1) are as follows:

- Pig weight at the diet change for each phase p , $X = (x_1, x_2, x_3 \dots x_{p_m-1})$, where x_p is the average pig live weight at which phase p is shifted to phase $p+1$
- Percentage of feed A in each phase p , $\alpha = (\alpha_1, \alpha_2, \alpha_3 \dots \alpha_{p_m})$, where α_p is the percentage of feed A in a blend used during phase p
- Target slaughter weight TW , which is the minimum live weight of a pig ready for slaughter. Pigs that have reached the target weight are selected for shipment to the slaughterhouse (individual marketing). Pigs that have not yet reached the target weight are kept until the next shipment, unless the maximum fattening duration has been reached.
- Maximum fattening duration (Max_d) which is the maximum allowed duration including cleaning and disinfecting time before the arrival of a new batch of pigs. When the maximum fattening duration is reached, all remaining pigs are sent to the slaughterhouse in the next shipment. Light

pigs that have not reached the target weight at the maximum fattening duration result in a lower payment.

2.3. Mathematical formulation of the bioeconomic model

To capture the complexity of the system studied, the simulation of each pig is not independent of one another because 1) pigs are allocated to pens by weight at the start of the fattening period, i.e. there are pens of light pigs and pens of heavy pigs. Consequently, pigs from the same pen are fed the same way (pigs stay in the same pen during all the period), but it differs at any given time between pens (when the average live weight of pigs in the pen equals pig weight at the diet change, the model moves to the next feeding phase); 2) the model incorporates a density function, which affects growth when the animal density in the considered pen is above a threshold.

Here, we present only the mathematical elements necessary to understand the optimization procedure. Tables 2, 3, and 4 provide indices, inputs, and quantities used in the bioeconomic model, respectively. The gross margin obtained from pig i of sex g is calculated as the selling price of pig i of sex g minus cost of piglet i of sex g minus feeding cost of pig i of sex g (Eq. 2):

$$GM^{ig}(X, \alpha, TW, Max_d) = FSP^{ig}(X, \alpha, TW, Max_d) - PGC^{ig} - FC^{ig}(X, \alpha, TW, Max_d). \quad (2)$$

The feeding cost of pig i of sex g results from the cost associated with the consumption of feeds A and B in each phase of the sequence (Eq. 3):

$$FC^{ig}(X, \alpha, TW, Max_d) = \sum_{p=1}^{p_m} \left[\sum_{d \in D_p^{ig}(X)} q_d^{ig} (\alpha_p * z_{p,1} + (1 - \alpha_p) * z_{p,2}) \right], \quad (3)$$

where:

$$D_1^{ig} = \{d: LW_d^{ig} < x_1\},$$

$$D_p^{ig} = \{d: x_{p-1} \leq LW_d^{ig} < x_p\}, 2 \leq p \leq p_{m-1},$$

$$D_{p_m}^{ig} = \{d: TW > LW_d^{ig} \geq x_{p_{m-1}}, d \leq Max_d\} \cup \{d: d_{TW}^{ig} < d < \min(d_s(d_{TW}^{ig}), Max_d)\}.$$

where D_p^{ig} is the vector of days belonging to the feeding phase p ($p=1...p_m$) for pig i of sex g , d_{TW}^{ig} is the day on which pig i of sex g reaches the target weight (TW), and $d_s(d_{TW}^{ig})$ is the day of the next

shipment following d_{TW}^{ig} . Feed intake (q_d^{ig}) is modeled as a gamma function of NE requirements for maintenance. This calculation is part of the InraPorc model included in the present model and described in details by van Milgen et al. (2008).

If the pig dies during the fattening period, its selling price equals zero. If not, the pig is slaughtered, and a premium or discount is added to the market price per kg of carcass weight. The premium or discount (ranging from -0.70 to 0.19 €/kg carcass weight) is determined from the carcass weight and lean percentage of pig i of sex g using a payment grid (Table S4 in Supplementary Material). This payment grid, which is described with threshold values to set the premium or discount, is a major source of discontinuity of the objective function. The selling price of pig i of sex g per kg of carcass weight is based on market price and the premium or discount. The carcass price paid to the farmer is based on the selling price SLP^{ig} and cold carcass weight CCW^{ig} (Eq. 4):

$$FSP^{ig}(X, \alpha, TW, Max_d) = SLP^{ig}(X, \alpha, TW, Max_d) * CCW^{ig}(X, \alpha, TW, Max_d). \quad (4)$$

The cost of piglet i of sex g at the entrance of the fattening unit is based on a fixed cost and an additional cost that depend on piglet weight:

$$PGC^{ig} = PP + ADP^{ig}(ILW^{ig}). \quad (5)$$

In our model, transportation cost is not included. Indeed, in France, most of the farms belong to a producer association that manages the transport of pigs to slaughterhouse. In this case, a single truck can get pigs from various farms. Transportation cost is supported by the producer association. There are some articles in the literature dealing with transportation cost in the objective function (Nadal-Roig et al., 2018; Nadal-Roig et al., 2019), but this is relevant for supply chain management problems with an integrator. Therefore, in this case, the objective function is about maximizing the profitability of the integrator itself and not for a single batch. The model is described in more detail in Supplementary Material (Tables S1 and S2).

2.4. Optimization approach

The optimization approach was developed to address two issues in the optimization of the bioeconomic model. The first issue was finding an appropriate algorithm to optimize the objective

function, which is discontinuous, non-convex, nonlinear, and multimodal (Leen et al., 2018; Dooyum et al., 2018; Accatino et al., 2019; Peña Fernández et al., 2019). The properties of the optimization function result mainly from the variability in pigs' biological characteristics, the occurrence of discrete events such as deliveries of pigs to the slaughterhouse, the stochasticity related to pig mortality, and the payment grid. An objective function with these features may have a large number of local optima, with the global optimum located near the local optima but in an area smaller than the entire search space (Hansen and Kern, 2010). In this situation, a global optimization algorithm is needed to prevent convergence towards the local optima (Dooyum et al., 2018). The second issue was to decrease the number of functions evaluations during optimization. Since the bioeconomic model simulates the growth of each pig for each day, the pig-fattening unit model requires large amounts of computational time (Cadero et al., 2018b), and running an optimization with it could take a long time. In this case, applying exact methods is not appropriate because they are extremely time-consuming processes (Jourdan et al., 2009; Puchinger and Raidl, 2005).

In order to model problems in pig farming systems, non-exact optimization algorithms have already been used (Morel et al., 2012; Lehmann et al., 2013; Britz and Kallrath, 2012; Accatino et al., 2019; Teillard et al., 2016; Groot et al., 2010; Groot and Rossing, 2011; Alexander et al., 2006). Among different evolutionary algorithms, the covariance matrix adaptation evolution strategy (CMA-ES) was chosen due to its ability to reach an excellent performance on the accuracy, its efficiency, and faster computing speed to deal with non-convex problems compared to other approaches (Hansen, 2006; Hansen and Kern, 2010). CMA-ES belongs to the family of genetic algorithms (Holland, 1973). In CMA-ES, the multivariate normal distribution used to sample potential solutions is used as the mutation operator, and a covariance matrix is used to reach regions with expected lower objective values. Therefore, any result obtained from CMA-ES is a pseudo-optimum or a good-enough approximation to the optimum as CMA-ES is a non-exact optimization method. The model is available open access on the Datainrae data warehouse (<https://doi.org/10.15454/OWJJUU>).

2.5. Model behavior and application

274 Multiple analyses were performed using the bioeconomic model coupled with the optimization
275 procedure aiming at 1) investigating the effect of the variability in pig growth performance, 2)
276 providing practical recommendations on how to use the optimization procedure, 3) illustrating the
277 potential of the optimization procedure to improve the profitability of a batch of pigs in a given
278 economic context, and 4) highlighting effects of pork price on optimal feeding and shipping strategies
279 (Table 5). To this end, optimization of a single batch without mortality rate was considered to reduce
280 the complexity of the problem and the computational time. Market prices for both pork and feed
281 ingredients are exogenous in the model. They are given as an input, with a single value for each,
282 referring to a given economic context. We used mean feed and pork prices over 2 years (2016 and
283 2017). The years 2016-2017 are medium situation for pork price (1.314 €/kg carcass whereas in 2019
284 it moved from 1.1 to 1.7 €/kg), and low feed price situation compared to 2014 (Notes de conjoncture
285 Aliment IFIP, 2016; Marché du Porc Breton, 2017). Further description of inputs common to all case
286 studies is available in Table S3 in Supplementary Material.

287 *Definition of different case studies.* All feeding strategies were based on feed A and feed B, which
288 were formulated on a least-cost basis to contain 9.75 MJ NE/kg and to meet 110% and 90% of the
289 average SID lysine requirement of female pigs at 30 and 120 kg BW, respectively. This approach
290 resulted in 1.05 and 0.47 g SID lysine/MJ NE in feed A and B, respectively (diet composition and
291 economic data for feeds A and B are shown in Table S5 in Supplementary material). The supply of
292 essential amino acids other than lysine met or exceeded ratios of the ideal protein profile. Feeds were
293 formulated through a least-cost linear programming prior to the optimization procedure. Therefore,
294 the feeds are inputs of the model.

295 Two case studies were first simulated to be considered as baselines representative of situations on
296 commercial farms:

- 297 - Reference one-phase R-1 in which a single-phase feeding strategy was simulated with feed A
298 supplied throughout the entire fattening period.

- Reference two-phase R-2, in which a two-phase feeding strategy was simulated with Growing (G) and Finishing (F) diets based on feeds A and B. Diet G (feed A only) was fed in the first phase from 70 days of age until a mean BW of 65 kg. In the second phase, diet F, supplied from 65 kg BW to the end of the fattening period, provided 0.76 g SID lysine/MJ NE, corresponding to 110% of the mean requirement at 65 kg BW. Diet F was obtained by mixing 54.7% of feed A and 45.3% of feed B (Figure 2). This case study corresponds to a typical two-phase feeding strategy used in practice in France (AGRESTE, 2008).

Six case studies were obtained through optimization using different sets of decision variables. The purpose of the different case studies was to investigate interactions between feeding and shipping strategies. For that reason, we first considered feeding and shipping strategies separately using different case studies. Then, we considered both strategies simultaneously (Table 6):

- Feeding case study F-1 (objective function (decision variables): $Obj(\alpha_1)$), in which a single-phase feeding strategy is optimized by mixing two feeds with low and high nutrient contents, respectively. The decision variable is the percentage of the first feed (α_1).
- Feeding case study F-2 (objective function (decision variables): $Obj(x_1)$), in which pig weight at the diet change (x_1) is optimized in a two-phase feeding strategy that used diets G and F.
- Feeding case study F-3 (objective function (decision variables): $Obj(x_1, \alpha_1, \alpha_2)$), in which a two-phase feeding strategy is obtained by mixing feeds A and B. The percentage of feed A in the first phase (α_1) and the second phase (α_2) are optimized, as is pig weight at the diet change (x_1) (three decision variables). This case study addresses all the decision variables for the feeding strategy.
- Shipping case study S-1 (objective function (decision variables): $Obj(TW, Max_d)$), in which the shipping strategy is optimized in a two-phase feeding strategy that used diets G and F. This case study explores when pigs must be sent to the slaughterhouse since over- and under-weight pigs affect the gross margin.

- Feeding and shipping case study FS-1 (objective function (decision variables): $Obj(x_1, \alpha_1, \alpha_2, TW)$) in which a two-phase feeding strategy is obtained by mixing feeds A and B, with four decision variables. Three decision variables are the same as those in F-3, and the fourth is the target weight at slaughter (TW). This new decision variable addresses the trade-offs among the increase in feed cost when keeping pigs longer, the risk of decreasing the premium per kg of carcass, and the potential increase in the selling price when shipping heavier pigs.

- Feeding and shipping case study FS-2 (objective function (decision variables): $Obj(x_1, \alpha_1, \alpha_2, TW, Max_d)$), in which a two-phase feeding strategy is obtained using feeds A and B, with five decision variables. Four decision variables are the same as those in FS-1, and the fifth is the maximum fattening duration (Max_d), which specifies when the fattening room must be emptied (i.e., all remaining pigs must be sent to the slaughterhouse). Increasing Max_d extends the fattening of light pigs. This case study will optimize both feeding and shipping strategies and all five decision variables.

Parameterization of the optimization procedure. All case studies that included the same decision variables used the same initial points for the CMA-ES algorithm: 50 kg for live weight at the diet change (x_1), 80% of feed A in the first and second phases (α_1, α_2), 120 kg for target weight (TW), and 108 days for the maximum fattening duration (Max_d). The criterion for stopping the iterations was the function tolerance. Iterations end when the range of the values of the best objective function of the last $10+4n$ (n is the number of decision variables) generations and all function values of the current generation are lower than the function tolerance. The default value of the CMA-ES algorithm (10^{-12}) was used for the results presented below. However, due to the limitation of function values to the second digit after the decimal point, the shape of the function, and the averaging performed for different choices of a set of pig profiles (different seeds of the pseudo random draw of the profiles), similar results are obtained with a less precise tolerance (10^{-6} , see Table S6 in Supplementary

349 Material). The optimization procedure was coded in Python 3.7 and run on an Intel Core i5 CPU (3.40
350 GHz).

351 *Analyses performed.* Four sets of analyses were performed (Table 5). The first explored model
352 properties. Since the variability in performance among pigs was assumed to generate discontinuity in
353 the objective function, we simulated case studies F-1 and F-2 with 10 or 400 pigs (which is the mean
354 size of a batch in France), while using either the same average pig profile for all pigs or randomly
355 choosing a different profile for each pig to generate the appropriate variability within the pig herd, as
356 described by Cadero et al. (2018a).

357 The second set of analyses provided practical recommendations for running an optimization (i.e.,
358 defining the number of random seeds (i.e. numbers used to initiate pseudorandom-number generator)
359 and the number of pigs per batch needed to run an optimization). To this end, we investigated the
360 trade-off between the reliability of results and the computational time by varying the number of pigs
361 per batch from 10 to 400 in F-2 and F-3. For each batch size, we used 60 different seeds to select
362 different sets of pig profiles to generate as much variability in the results as possible. Python
363 *random.seed* method was used to generate a pseudo-random number for selecting different sets of pig
364 profiles. Each seed value corresponds to a sequence of generated values for a given random number
365 generator. For this stage, 60 different seed values for each case study (F-2 and F-3) and for each
366 number of pigs (10 up to 400 pigs) were chosen randomly. Effects of the number of pigs on the mean
367 gross margin per pig and the computational time were analyzed using a one-way analysis of variance
368 (ANOVA). The post-hoc Tukey Honestly Significant Difference (HSD) test was used to identify a
369 significant difference between means at a significance level of 5%. We also investigated the effect of
370 the number of seeds and the number of pigs in the simulated batch on the coefficient of variation
371 (CV) of the gross margin.

372 The third set of analyses illustrated the ability of the optimization procedure to improve the
373 profitability of pig-fattening units. It also provided the environmental impacts of the production
374 associated with each case study. All reference case studies (R-1 and R-2) and optimization case

375 studies (F-1 to FS-2) were run with the number of seeds and the batch size recommended from the
376 second set of analyses. For each case study, the same sequence of generated values issued from a
377 given seed number was used.

378 The fourth set of analyses explored the effect of pork price on the mean gross margin per pig and
379 optimal feeding and shipping strategies. We assumed that farmers have the possibility of buying feeds
380 and selling pigs in advance (with forward or futures contracts) and these prices are fixed for a batch
381 of pigs. However, pork price will change over the year and will be different for the next batch of pigs.
382 Therefore, we considered three different pork prices representing low (1.173 €/kg), medium (1.314
383 €/kg, the one used in the first three sets of analyses), and high price (1.662 €/kg) situations. These
384 values were mean values of pork price over May to July 2018 (1.173 €/kg), years 2016-17 (1.314
385 €/kg), and August to October 2019 (1.662 €/kg). For each pork price, R-2 and optimization case
386 studies F-3, S-1, FS-1, and FS-2 were run with the same number of seeds and same batch size as those
387 in the third set of analyses. Effects of all case studies (optimized and simulated) on mean gross margin
388 per pig, decision variables, computational time, and technical outputs were tested with a one-way
389 ANOVA. We again **used** the post-hoc Tukey HSD test to identify a significant difference between
390 means at a significance level of 5%.

391

392 **3. Results**

393 *3.1 Exploration of model properties*

394 The effect of the percentage of feed A in the diet on the mean gross margin per pig was explored in
395 F-1 (Figure 3). As we expected, without variability among pigs, the response of the gross margin to
396 the percentage of feed A in the diet was not affected by the number of pigs per batch (10 vs. 400) in
397 the simulation. A jump discontinuity occurred, however, when the percentage of feed A increased
398 from 30.3% (point Q in Figure 3, with mean gross margin of 28.39€/pig) to 30.4% (point P in Figure
399 3, with mean gross margin of 30.17€/pig). In both case studies, all pigs were kept on the farm until
400 the end of the fattening period, since no pig reached the required live weight at slaughter. The

401 corrected lean percentage for each pig was 61.01% for point Q and 60.99% for point P. Thus, different
402 premiums were obtained according to the payment grid (Table S4). This discontinuity was due to the
403 difference between premiums in the two case studies. By including the biological variability among
404 pigs, the response of mean gross margin per pig to the percentage of feed A was clearly discontinuous
405 for the simulation with 10 pigs. Increasing the number of pigs (400 pigs), however, reduced
406 discontinuity.

407 The effect of the live weight at the diet change on the mean gross margin per pig was explored in F-
408 2 (Figure 4). Without variability among pigs, the response of gross margin to live weight at diet
409 change was nearly continuous and again not influenced by the number of pigs in the simulation. The
410 optimum live weight at diet change was 47 kg for both sizes of the batch. When simulating 10 pigs
411 and considering biological variability among them, the response of gross margin to live weight at diet
412 change was clearly discontinuous. Discontinuity was dramatically reduced with 400 pigs in the
413 simulation. The gross margin was always lower with variability among pigs than without variability
414 among pigs, and the gross margin had many local optima when simulating 10 pigs (Figures 3 and 4).

415 *3.2 Providing users' recommendations*

416 In F-2, the number of pigs per batch did not influence the mean gross margin per pig (Figure 5).
417 However, increasing the number of pigs in the batch reduced the standard deviation, and decreased
418 the difference between the mean and median, of the gross margin. Although increasing the number
419 of pigs provided more consistent results, it also required longer computational time (Figure 6).
420 Moreover, the variability in computational time increased significantly ($p < 0.05$) with the number of
421 pigs in the batch (Figure 6).

422 In F-3, the number of pigs per batch did not influence the mean gross margin per pig ($p > 0.05$).
423 Optimizing three decision variables required 2.5 fold as much computational time as was required to
424 optimize one decision variable in F-2. In F-3, increasing the number of pigs reduced the CV of the
425 optimized gross margin and increased ($p < 0.05$) computational time (Figures 8 and S1 and S2 in
426 supplement material).

427 In F-3, regardless of the number of seeds, the CV of gross margin decreased exponentially from 14-
428 16% to a minimum of 2% as the number of pigs increased, and the mean gross margin stabilized
429 when the batch contained at least 200 pigs (Figure 7). Moreover, no significant differences were
430 observed in the means of decision variables obtained with more than 20 seeds and 200 pigs ($P>0.05$).
431 Consequently, the third set of analyses was performed with 20 seeds and 200 pigs per batch.

432 *3.3 Model potentials*

433 Table 7 compares the mean gross margin per pig, decision variables, and technical outputs obtained
434 in the simulation and optimization case studies. With a one-phase feeding strategy, optimizing the
435 percentage of feed A in the blend increased the gross margin by 4.0 €/pig (29.28 €/pig in F-1 vs. 25.26
436 €/pig in R-1). It also decreased the percentage of feed A (49% in F-1 vs. 100% in R-1) and the mean
437 slaughter weight (115.1 kg/pig in F-1 vs. 116.1 kg/pig in R-1).

438 With a two-phase feeding strategy, optimizing pig weight at the diet change (F-2) increased the gross
439 margin by 0.9 €/pig compared to R-2, while it decreased pig weight at the diet change from 65 kg to
440 38 kg. The number of decision variables increased from one to five when comparing F-2 to FS-2.
441 Each increase in the number of decision variables increased the gross margin per pig (from 29.3 €/pig
442 in F-2 to 31.3 €/pig in FS-2) and the computational time (from 11.3 min in F-2 to 53.7 min in FS-2).
443 When optimizing only the feeding strategy (F-2 and F-3), mean slaughter weight remained nearly
444 stable and did not differ significantly from that in R-2. Optimizing only the shipping strategy (S-1)
445 increased the selling price and feed cost (€/pig). Optimizing both feeding and shipping strategies
446 reduced the dietary digestible lysine content by 10-15% in FS-1 and FS-2 compared to that in R-2. In
447 FS-1, optimizing the target slaughter weight yielded a mean slaughter weight of 117 kg.
448 Consequently, revenue from selling pigs and the gross margin improved. In FS-2, optimizing the
449 maximum fattening duration increased mean slaughter weight by an additional 3.7 kg, revenue per
450 pig, and the resulting gross margin. The optimized percentages of feed A in phases 1 (from 69.4% to
451 72.8%) and 2 (from 40.2% to 46.8%) and pig weight at the diet change were stable in F-3, FS-1, and

452 FS-2. The mean gross margin per pig increased much more when optimizing both feeding and
453 shipping strategies (FS-1 and FS-2) than when optimizing just one strategy.
454 Table 8 compares the environmental results obtained in the simulation and optimization case studies.
455 With a one-phase feeding strategy, climate change (-8%), acidification (-13%), eutrophication (-
456 11.5%), and cumulative energy demand (-13.5%) decreased in F-1 compared to those in R-1 ($p < 0.05$).
457 However, land occupation increased (3.84 m² year in F-1 vs. 3.72 m² year in R-1). With a two-phase
458 feeding strategy, optimizing either the feeding strategy or both feeding and shipping strategies (F-2
459 up to FS-2) reduced the environmental impacts except land occupation. Conversely, when optimizing
460 only the shipping strategy (S-1), all impacts increased compared to those in R-2 ($p < 0.05$).

461 *3.4 Level changes in pork price*

462 Figure 8 shows effects of pork price on the mean gross margin per pig and technical outputs obtained
463 in R-2, F-3, S-1, FS-1, and FS-2 strategies. Relative benefit (calculated as the mean gross margin of
464 each optimization case study minus the mean gross margin of R-2) from optimization increased with
465 increasing pork price except for F-3. Indeed, when increasing pork price, the revenue from selling
466 pigs in R-2 increased more than that in F-3 because slaughter weight in F-3 was lower than that in R-
467 2. Figure 9 shows the effects of pork price on decision variables obtained in the various case studies.
468 Optimizing only the shipping strategy (S-1) increased the target weight and maximum fattening
469 duration, which increased slaughter age and weight. Therefore, S-1 had the highest feed cost (€/pig).
470 The optimization procedure in FS-1 increased the percentage of feed A in both phases. However, pig
471 weight at the diet change decreased as pork price increased. As a result, feed cost (€/pig) and slaughter
472 weight remained rather stable with increasing pork price. The pork price had effects on slaughter
473 weight, premium, and feed cost (€/pig) only when optimizing the maximum fattening duration (S-1
474 and FS-2). Relative benefit increased much more when optimizing both feeding and shipping
475 strategies (FS-1 and FS-2) than when optimizing just one strategy.
476 Figure 10 shows the **variation of gross margin and environmental impacts according to pork price in**
477 **FS-2, i.e. the trade-off between economic and environmental outputs. With medium pork price**

(1.314€/kg), environmental impacts remained stable relatively to the low pork price situation (1.173 €/kg) while gross margin increased by 18%. With high pork price (1.662 €/kg), all environmental impacts increased compared to those in low pork price (1.173 €/kg) situation, by 1.5% to 2.7%: climate change (2.1%), acidification (2.7%), eutrophication (2.6%), cumulative energy demand (1.5%), and land occupation (2.3%).

4. Discussion

The objective of this study was to develop a bioeconomic model for the optimization of feeding and shipping strategies for a batch of fattening pigs in order to maximize profitability. We used an individual-based growth model to consider the variability in performance among pigs. To this end, the model developed by Cadero et al. (2018a) was used. However, the bioeconomic model of Cadero et al. (2018a) was a simulation model, which does not allow us to find the optimal feeding and shipping strategies. Therefore, advantages of the present model are to 1) maximize the economic performance of a batch of pigs, and 2) identify the best feeding and shipping strategies in a given economic context. Our approach considers both strategies and the variability in pig growth performance simultaneously, which was not previously made in the literature (Niemi (2006) only used an average pig growth model). However, the optimization process with such a model is challenging because of the complexity of decisions and discontinuous nature of the objective function.

In the next sections, we discuss ability of the model to simulate the effect of variability among pigs and its added-value. We provide practical recommendations on the use of the optimization procedure in the bioeconomic model (number of pigs, number of seeds). Then, we evaluate its potential to identify optimal strategies that improve the profitability of a batch of pigs. We also discuss how the level of pork price modifies the optimal feeding and shipping strategies. Last, we analyze the consequences of economic optimization on the environmental impacts of pig production.

4.1. Ability of the model to simulate the effect of variability among pigs

504 The first set of analyses using the optimization procedure highlighted the discontinuous nature of the
505 mean gross margin per pig depending on the decision variables, and the relevance of variability
506 among pigs in the model to simulate the economic outputs of the batch. This discontinuity of the
507 objective function results from the various factors and processes modeled: 1) the use of the payment
508 grid to calculate the selling price of each pig, 2) the scheduling of deliveries of pigs to the
509 slaughterhouse, and 3) the variability among pigs. The payment grid defines the premium or discount
510 for a given pig according to fixed thresholds for carcass weight and lean percentage. Therefore, a
511 minor change in a decision variable could change the premium or discount for the pig considered and
512 result in discontinuity. We observed this discontinuity of the objective function in the first set of
513 analyses, even if we simulated the bioeconomic model without variability among the pigs (Figure 3).
514 These results agree with those of Leen et al. (2018) who showed discontinuous evolution caused by
515 carcass payment grid. In the bioeconomic model, deliveries to the slaughterhouse are scheduled once
516 a week according to the farmer's estimate of each pig's live weight and the number of pigs that
517 reached the target slaughter weight. Hence, a minor change in a decision variable can change a pig's
518 weight status, which can delay its delivery to the slaughterhouse for one week.

519 Without biological variability among pigs, all pigs had the same growth performance and carcass
520 traits and thus were sent together to the slaughterhouse. In this case, one shipment per batch was
521 performed, which is not consistent with the reality of commercial farms, which usually have at least
522 three shipments per batch (Aubry et al., 2016). Considering between-animal variation in the pig
523 growth model resulted in different feeding and shipping practices for each pig and a decrease in the
524 gross margin. These results, already suggested by Cadero et al. (2018a) and Brossard et al. (2009),
525 clearly support the use of a growth model accounting for variability among pigs. Indeed, Figures 3
526 and 4 show that 1) not considering variability in animal performance results in overestimating
527 economic results, and 2) when considering variability in pig performance, optimal strategies are
528 different from the one obtained with an average pig growth model. For instance in Figure 3, with 400
529 pigs, the optimal percentage of feed A without variability was between 42.5% and 44%, whereas the

530 optimal percentage was 51% when considering variability. In Figure 4, with 400 pigs, the optimal pig
531 weight at the diet change without variability was 47 kg, whereas the optimal pig weight at the diet
532 change with variability was 38 kg. These results also agree with those of Conte et al. (2011), Niemi
533 et al. (2010), and Rodríguez-Sanchez et al. (2018), who indicated that the gross margin decreased
534 when animal variability within herds increased. Considering variability among pigs also contributes
535 to the discontinuous nature of the objective function of the bioeconomic model, because the random
536 pig profiles can differ greatly from each other and result in different economic results depending on
537 the decision variables.

538 Considering variability in performance among pigs at the batch level means that the optimal time of
539 marketing may be different for each pig. Kristensen et al. (2012) considered the optimization of
540 marketing pigs at the pen level. They assumed that the first possible week of slaughter was week 9
541 after the beginning of fattening. Once a week, they selected k heaviest pigs and sent them to the
542 slaughterhouse. In the present study, the shipping strategy is applied over the whole batch of pigs
543 considering the different pens. When the target slaughter weight is not optimized in our approach, the
544 selection procedure of pigs to be slaughtered is rather similar to the one used by Kristensen et al.
545 (2012), unless it is applied at the batch level. Our approach offers the additional opportunity to
546 optimize simultaneously the slaughter target weight. Using a hierarchical Markov decision process,
547 Pourmoayed et al. (2016) also optimized feeding and shipping strategies at the pen level (15 pigs)
548 with different genetic properties of pigs in each pen. They also showed that optimal feeding strategy
549 (time at diet change in a three-phase feeding program) and optimal time at shipping, differed between
550 pens with different genetic potential. Compared to the model from Pourmoayed et al. (2016), the
551 present model offers the possibility to modulate the proportion of each feed in each pen at each phase
552 and predicts the response of pigs to these changes, on the basis of the individual growth model,
553 whereas in Pourmoayed et al. (2016) time series of pig weights and feeding are obtained from online
554 monitoring. Figures 3 and 4 compare optimal strategies at pen level (10 pigs) with those at batch level
555 (400 pigs, 20 pens with 20 pigs per pen). In Figure 3, the optimal percentage of feed A with one pen

(10 pigs) was 55.5%, whereas the optimal percentage of feed A was 51% at the batch level (400 pigs). In Figure 4, the optimal pig weight at the diet change was 43 kg at the pen level (10 pigs), whereas the optimal pig weight at the diet change at the batch level (400 pigs) was 38 kg. Since the optimal strategies at the pen level differed from those observed at the batch level, ignoring variability between pens might change optimal feeding and shipping strategies and consequently reduce the profitability of a batch of pigs.

4.2 Application of the optimization procedure

The purpose of the second set of analyses was to find the adequate number of pigs and seeds to run the optimization procedure, in order to avoid too much discontinuity in the objective function, to reach acceptable stability and accuracy of predictions, while limiting computational time. Increasing the number of pigs per batch reduces the discontinuity of the objective function because a single pig profile that differs greatly from the average profile has less impact on the batch result when included in a batch of 100 pigs than in a batch of 10 pigs. The decrease in the discontinuity and complexity of changes in the gross margin may be due to averaging effects. As a result, the computational time increased, but the number of functions evaluations decreased. The computational time increased mainly due to simulating the growth of each pig individually. Consequently, it was necessary to analyze relationships between the number of pigs per batch, the number of seeds used to run the optimization, and the variability in mean gross margin per pig. Results of F-2 and F-3 indicated that increasing the number of pigs per batch tended to decrease variability in the gross margin per pig but required longer computational time. The CV of the gross margin per pig remained low and stable with a batch size of 200-400 pigs. The number of seeds had little effect on the mean and CV of gross margin per pig. Optimization with only 10 seeds resulted in a slightly higher CV of mean gross margin per pig (only with 10 pigs), while the mean gross margin per pig differed only slightly from those observed with 20-60 seeds. Consequently, the optimization procedure in future studies should include at least 200 pigs per batch and 20 seeds.

4.3 Optimization of feeding and shipping strategies

Results of the third set of analyses highlighted that the economic optimum differs from the technical optimum. This is consistent with other studies observing that maximizing profitability differs from maximizing growth performance, and implies not meeting the nutrient requirements of all pigs (Chiba, 2000; Van Heugten, 2010; Niemi et al., 2010; Pomar and Remus, 2019). R-2 supplied 110% of the mean population requirement in digestible lysine at the start of each phase. This level of lysine meets the requirements of most pigs to express their growth potential, regardless of the economic aspects (Brossard et al., 2009). Optimizing the feeding strategy (F-3); however, decreased the digestible lysine supply (from 10.05 g/kg in R-2 to 8.42 g/kg in F-3 for the first phase, and from 7.62 g/kg in R-2 to 6.95 g/kg in F-3 for the second phase) and also decreased pig weight at the diet change. It increased slaughter age and decreased average daily gain, slaughter weight, and lean percentage. Consequently, feed cost (€/pig) in F-3 was lower than that in R-2. Indeed, satisfying the need of all pigs requires supplying more feed A (rich diet), which is more expensive than feed B (poor diet). These results highlight the trade-off between feed cost and technical performance in the optimization procedure.

When optimizing the target weight in addition to the feeding strategy (FS-1), target weight increased and gross margin per fattened pig improved by 6.84% compared to R-2. However, slaughter weight increased only for fast-growing pigs. Slow-growing pigs were delivered to the slaughterhouse at the end of the fattening duration and resulted in a discount. By optimizing target weight and the maximum fattening duration (FS-2 and S-1), the mean gross margin per pig improved, which is consistent with the results of Leen et al. (2018). This result may be explained by increased slaughter weight and premiums of slow-growing pigs. In the economic context used, extending the fattening duration (FS-2) had a better outcome for the total gross margin per batch. However, the maximum fattening duration is a decision variable, which should be considered with care. On most farrow-to-finish farms, the maximum fattening duration is rather a constraint related to the number of rooms and the batch management system. This means that when performing the optimization, if modifying the maximum fattening duration, the gross margin per pig and per day should be examined as well. Optimizing only

608 the feeding strategy (F-3) decreased feed cost (€/pig) and slaughter weight while optimizing only the
609 shipping strategy (S-1) increased feed cost (€/pig) and slaughter weight. These results highlighted
610 that the trade-off between reducing feeding cost (feeding strategy) and delivering heavier pigs
611 (shipping strategy) must be considered to benefit fully from the potential of the batch of pigs.
612 Optimizing feeding and shipping strategies simultaneously provided more benefits for the pig-
613 fattening than optimizing only one strategy. Moreover, optimizing the shipping strategy at the same
614 time modified the optimal feeding strategy, which indicates that the bioeconomic model and
615 optimization procedure also consider the interaction between the feeding and shipping strategies. This
616 is the first time that a bioeconomic model of the pig-fattening unit, coupled with an optimization
617 procedure, was able to optimize both feeding and shipping strategies while also considering the
618 influence of the variability in performance among a batch of pigs. This is of high relevance because:
619 1) interactions between feeding strategies, shipping strategies, and the variability in pig growth
620 performance largely determine the profitability of the batch of pigs; 2) optimal decisions and gross
621 margin are very different from the one obtained with an average pig growth model. This is one
622 contribution to the literature because most previous models optimized either the feeding (Morel et al.,
623 2012) or shipping strategy (Nadal-Roig et al., 2018; Leen et al., 2018), or both strategies, but with a
624 model of the average pig (Niemi, 2006). However, some of the model's decisions are based on
625 information that might be difficult to obtain on farms. For instance, weights of pigs are required to
626 decide the time of diet change or to forecast pig shipping to the slaughterhouse. In practice, farmers
627 may use weighting scales to sort the pigs before shipping, but this is time-consuming, and most often,
628 they perform visual estimation of body weight. In the same way, there is also some uncertainty on
629 the feed composition. For the future, it could thus be interesting to include this uncertainty in the
630 model. However, thanks to the development of precision farming, this uncertainty should drastically
631 reduce with the use of equipment and sensors providing real-time information on characteristics of
632 pigs and their environment (Vranken and Bermans, 2017).

633 *4.4 Effects of pork price on optimal feeding and shipping strategies*

Results of the fourth set of analyses allowed us to study the effect of changes in pork price on optimal feeding and shipping strategies. The pork price had a minor impact on decision variables associated with feeding strategies when optimizing only the feeding strategy (F-3). However, when optimizing either shipping or both shipping and feeding strategies, pork price had a major impact on shipping decisions. Indeed, shipping decision variables (TW and Max_d) increased as pork price increased. When optimizing both feeding and shipping strategies (FS-1 and FS-2), effects of pork price on the optimal feeding strategy varied. As pork price increased, the optimization procedure in FS-1 supplied richer diets (including more feed A) than those in other case studies. However, since the optimization procedure in FS-2 extended the maximum fattening duration (Max_d) with increasing pork price, the amount of feed A in diets decreased at the same time to avoid increasing diet costs. This behavior of the optimization procedure highlights interactions between pork price and both types of strategies. Therefore, this indicates that our model is able to handle the effects of the economic context on optimal strategies.

The purpose of the present paper was mainly the development of the optimization model and the identification of an adequate procedure for using it. However, the optimization was performed assuming that the pork price and feed cost are perfectly known. Although this is correct in the context of forward or futures contracts, it is not right for long periods. For future studies, this raises the question of the sensitivity of the optimal feeding and shipping strategies to the uncertainty of pork and feed price and also piglets cost.

4.5 Environmental impacts

Since balancing economic outputs and the environmental impacts is a big challenge for pig production, we examined the effect of economic optimization of pig-fattening on the environment burden. When optimizing only the feeding strategy, global warming potential and eutrophication decreased, but land occupation increased. These reductions in environmental impacts may be explained by decreasing the amount of feed A (high nutrient density), which is consistent with the results of Van Heugten (2010) and Monteiro et al. (2017). Conversely, when the shipping strategy is

660 optimized, especially maximum fattening duration, improving the gross margin resulted in an
661 increase of all environmental impacts. These results showed that optimizing feeding and shipping
662 strategies simultaneously may inconsistently affect the different categories of environmental impacts.
663 When exploring the effects of pork price on both gross margin and environmental impacts (Figure
664 10), we highlighted that with a high pork price, improving the mean gross margin per pig increased
665 all environmental impacts, relatively to a low pork price situation. This result is explained by the fact
666 that pigs stayed longer on farms, and consequently consumed more feed, excreted more nutrients that
667 resulted in higher emissions. Therefore, further work should include multiobjective optimization in
668 order to address the trade-off between economic and environmental objectives.

669

670 5. Conclusions

671 Economic optimization of pig-fattening has received substantial attention since the demand for pork
672 products is expected to increase by 37% over the period 2010-2050. In this paper, we demonstrated
673 interactions between feeding and shipping strategies while considering the variability in
674 performances among pigs. We combined two tools, a bioeconomic model of pig-fattening and an
675 optimization procedure which is able to maximize the mean gross margin per pig in a given economic
676 context. To our knowledge, this is almost the first tool able to optimize both feeding and shipping
677 strategies while considering effects of variability in growth potential among a batch of pigs. These
678 features allow considering the interaction effect of feeding and shipping strategies on the economic
679 and environmental outputs of the batch, and investigation of the trade-off between production cost
680 and technical performance. Optimizing the shipping strategies modified the optimal feeding strategies
681 and resulted in more economic benefit than optimizing only one type of strategy. Pork price had a
682 limited effect on feeding decisions when optimized alone, but a strong impact on shipping decisions.
683 This tool should interest the pig sector since it can identify the best feeding and shipping strategies
684 depending on the economic context. The major concern for European pig production for the coming
685 years is coping with both economic and environmental challenges. In the present study, we

686 investigated the effect of economic optimization of pig-fattening on the environment burden. We
687 highlighted that economic optimization may increase environmental impacts. Therefore, in order to
688 balance economic and environmental outputs, further work should consider multiobjective
689 optimization with both economic and environmental objectives. Since feed has a major contribution
690 to impacts, including feed formulation throughout the entire optimization process will give more
691 opportunity to reduce environmental impacts.

692

693

694 **Acknowledgements**

695 This project received funding from INRAE metaprogram GloFoods and from the Brittany region
696 (grant for PhD of M. Mohsen Davoudkhani) of France.

697

698 **Software and data repository resources**

699 The code to run all the case studies described in this paper is accessible on the Datainrae data
700 warehouse (<https://doi.org/10.15454/OWJJUU>).

701

702 **REFERENCES**

703

- 704 Accatino, F., Tonda, A., Dross, C., Léger, F., Tichit, M., 2019. Trade-offs and synergies between
705 livestock production and other ecosystem services. *Agric. Syst.* 168, 58-72.
706 <https://doi.org/10.1016/j.agsy.2018.08.002>.
- 707 AGRESTE, 2008. Enquête sur les bâtiments d'élevage porcin de novembre 2008. Retrieved on 27
708 November 2019 at http://www.agreste.agriculture.gouv.fr/IMG/pdf_porcin2010T5.pdf.
- 709 AHDB, 2018. 2018 pig cost of production in selected countries. Retrieved on 3 June 2020 at
710 <https://ahdb.org.uk/knowledge-library/2018-pig-cost-of-production-in-selected-countries>.
- 711 Alexander, D.L.J., Morel, P.C.H., Wood, G.R., 2006. Feeding strategies for maximising gross margin
712 in pig production. In: Pinter, J.D. (Ed.), *Nonconvex Optimisation and its Application. Global
713 Optimisation Scientific and Engineering Case Studies*, vol. 85. , Springer, US, pp. 33–43.
- 714 Ali, B.M., Berentsen, P.B.M., Bastiaansen, J.W.M., Oude Lansink, A., 2018. A stochastic bio-
715 economic pig farm model to assess the impact of innovations on farm performance. *Animal* 12,
716 819-830. <https://doi.org/10.1017/s1751731117002531>.
- 717 Andretta, I., Pomar, C., Kipper, M., Hauschild, L., Rivest, J., 2016. Feeding behavior of growing-
718 finishing pigs reared under precision feeding strategies. *J. Anim. Sci.* 94, 3042-3050.
719 <https://doi.org/10.2527/jas.2016-0392>.

720 Aubry, A., Lescot, M., Cadero, A., Garcia-launay, F., Correge, I., Quiniou, N., 2016. La gestion des
721 fins de bande en élevage porcin : analyse des stratégies décisionnelles des éleveurs et des enjeux
722 économiques associés 225-230.

723 Britz, W., & Kallrath, J., 2012. Economic simulation models in agricultural economics: the current
724 and possible future role of algebraic modeling languages. In *Algebraic Modeling Systems* (pp.
725 199-212). Springer, Berlin, Heidelberg.

726 Brossard, L., Dourmad, J.-Y., Rivest, J., Van Milgen, J., 2009. Modelling the variation in
727 performance of a population of growing pig as affected by lysine supply and feeding strategy.
728 *Animal* 3, 1114-1123. <https://doi.org/10.1017/S1751731109004546>.

729 Brossard, L., Vautier, B., Van Milgen, J., Salaün, Y., & Quiniou, N., 2014. Comparison of in vivo
730 and in silico growth performance and variability in pigs when applying a feeding strategy
731 designed by simulation to control the variability of slaughter weight. *Animal Production Science*,
732 54(12), 1939-1945.

733 Cadero, A., Aubry, A., Brossard, L., Dourmad, J. Y., Salaün, Y., & Garcia-Launay, F., 2018a.
734 Modelling interactions between farmer practices and fattening pig performances with an
735 individual-based model. *Animal*, 12(6), 1277-1286.
736 <https://doi.org/10.1017/S1751731117002920>.

737 Cadero, A., Aubry, A., Brun, F., Dourmad, J. Y., Salaün, Y., & Garcia-Launay, F., 2018b. Global
738 sensitivity analysis of a pig fattening unit model simulating technico-economic performance and
739 environmental impacts. *Agricultural Systems*, 165, 221-229.
740 <https://doi.org/10.1016/J.AGSY.2018.06.016>.

741 Cadero, A., Aubry, A., Dourmad, J. Y., Salaün, Y., & Garcia-Launay, F., 2018c. Towards a decision
742 support tool with an individual-based model of a pig fattening unit. *Computers and Electronics in*
743 *Agriculture*, 147, 44-50. <https://doi.org/10.1016/j.compag.2018.02.012>.

744 Chiba, L. I., 2000. Feeding systems for pigs. *Feeding systems and feed evaluation models*. CABI
745 Publishing, Wallingford, UK, 189-209.

746 Conte, S., Boyle, L.A., O'Connell, N.E., Lynch, P.B., Lawlor, P.G., 2011. Effect of target slaughter
747 weight on production efficiency, carcass traits and behaviour of restrictively-fed gilts and intact
748 male finisher pigs. *Livest. Sci.* 136, 169-174. <https://doi.org/10.1016/j.livsci.2010.08.018>.

749 Dooyum, U.D., Mallipeddi, R., Pamulapati, T., Park, T., Kim, J., Woo, S., Ha, Y., 2018. Interactive
750 livestock feed ration optimization using evolutionary algorithms. *Comput. Electron. Agric.* 155,
751 1-11. <https://doi.org/10.1016/j.compag.2018.08.031>.

752 Dourmad, J. Y., Sève, B., Latimier, P., Boisen, S., Fernandez, J., Van der Peet-Schwering, C., &
753 Jongbloed, A. W., 1999. Nitrogen consumption, utilisation and losses in pig production in France,
754 The Netherlands and Denmark. *Livestock Production Science*, 58(3), 261-264.

755 FAO, 2017. *World Livestock (2017) – Livestock in food security*. FAO.

756 Gous, R.M., Berhe, E.T., 2006. Modelling populations for purposes of optimization. In: Gous, R.M.,
757 Morris, T., Fisher, C. (Eds.), *Mechanistic Modelling in Pig and Poultry Production*. CAB
758 International, pp. 76-96.

759 Groot, J.C.J., Jellema, A., Rossing, W.A.H., 2010. Designing a hedgerow network in a
760 multifunctional agricultural landscape: Balancing trade-offs among ecological quality, landscape
761 character and implementation costs. *Eur. J. Agron.* 32, 112–119.
762 <https://doi.org/10.1016/j.eja.2009.07.002>.

763 Groot, J.C.J., Rossing, W.A.H., 2011. Model-aided learning for adaptive management of natural
764 resources: an evolutionary design perspective. *Methods Ecol. Evol.* 2, 643–650.
765 <https://doi.org/10.1111/j.2041-210X.2011.00114.x>.

766 Hansen, N., 2006. The CMA Evolution Strategy: A Comparing Review, in: Lozano, J.A., Larrañaga,
767 P., Inza, I., Bengoetxea, E. (Eds.), *Towards a New Evolutionary Computation: Advances in the*
768 *Estimation of Distribution Algorithms*. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 75-
769 102. https://doi.org/10.1007/3-540-32494-1_4.

770 Hansen, N., Kern, S., 2010. Evaluating the CMA Evolution Strategy on Multimodal Test Functions
771 282-291. https://doi.org/10.1007/978-3-540-30217-9_29.

772 Holland, J. H., 1973. Genetic algorithms and the optimal allocation of trials. *SIAM Journal on*
773 *Computing*, 2(2), 88-105.

774 Joannopoulos, E. 2018. Contributions à la résolution globale de problèmes bilinéaires appliqués à
775 l'industrie porcine. Optimisation et contrôle [math.OC]. Thèse de doctorat INSA de Rennes,
776 Français. NNT:2018ISAR0006 tel-01885186

777 Joannopoulos, E., Dubeau, F., Dussault, J.-P., Pomar, C., 2015. Diet Problems. In: Plà-Aragonès,
778 L.M. (Ed.), *Handbook of Operations Research in Agriculture and the Agri-Food Industry*.
779 Springer New York, New York, NY, pp. 397-417.

780 Jourdan, L., Basseur, M., Talbi, E.G., 2009. Hybridizing exact methods and metaheuristics: A
781 taxonomy. *Eur. J. Oper. Res.* 199, 620-629. <https://doi.org/10.1016/j.ejor.2007.07.035>.

782 Kristensen, A.R., Nielsen, L., Nielsen, M.S., 2012. Optimal slaughter pig marketing with emphasis
783 on information from on-line live weight assessment. *Livest. Sci.* 145, 95-108.
784 <https://doi.org/10.1016/J.LIVSCI.2012.01.003>.

785 Leen, F., Van den Broeke, A., Aluwé, M., Lauwers, L., Millet, S., Van Meensel, J., 2018.
786 Stakeholder-driven modelling the impact of animal profile and market conditions on optimal
787 delivery weight in growing-finishing pig production. *Agric. Syst.* 162, 34-45.
788 <https://doi.org/10.1016/j.agsy.2018.01.013>.

789 Lehmann, N., Finger, R., Klein, T., Calanca, P., & Walter, A., 2013. Adapting crop management
790 practices to climate change: Modeling optimal solutions at the field scale. *Agricultural Systems*,
791 117, 55-65.

792 López-Vergé, S., Gasa, J., Temple, D., Bonet, J., Coma, J., Solà-Oriol, D., 2018. Strategies to improve
793 the growth and homogeneity of growing-finishing pigs: Feeder space and feeding management.
794 *Porc. Heal. Manag.* 4, 1-9. <https://doi.org/10.1186/s40813-018-0090-9>.

795 Marché du Porc Breton, 2017. Retrieved on 20 March 2020 at <https://www.marche-porc-breton.com>.

796 McAuliffe, G.A., Chapman, D.V., Sage, C.L., 2016. A thematic review of life cycle assessment
797 (LCA) applied to pig production. *Environmental Impact Assessment Review* 56, 12-22.

798 Monteiro, A.N.T.R., Bertol, T.M., de Oliveira, P.A.V., Dourmad, J.-Y., Coldebella, A., Kessler,
799 A.M., 2017. The impact of feeding growing-finishing pigs with reduced dietary protein levels on
800 performance, carcass traits, meat quality and environmental impacts. *Livest. Sci.* 198, 162-169.
801 <https://doi.org/10.1016/J.LIVSCI.2017.02.014>.

802 Morel, P. C. H., Sirisatien, D., & Wood, G. R., 2012. Effect of pig type, costs and prices, and dietary
803 restraints on dietary nutrient specification for maximum profitability in grower-finisher pig herds:
804 A theoretical approach. *Livestock Science*, 148(3), 255-267.

805 Nadal-Roig, E., Pagès-Bernaus, A., Plà-Aragonès, L.M., 2018. Bi-objective optimization model
806 based on profit and CO₂ emissions for pig deliveries to the abattoir. *Sustain.* 10, 1-13.
807 <https://doi.org/10.3390/su10061782>.

808 Nadal-Roig, E., Plà-Aragonès, L.M., Alonso-Ayuso, A., 2019. Production planning of supply chains
809 in the pig industry. *Comput. Electron. Agric.* 161, 72-78.
810 <https://doi.org/10.1016/J.COMPAG.2018.08.042>.

811 Niemi, J. K., Sevón-Aimonen, M. L., Pietola, K., & Stalder, K. J., 2010. The value of precision
812 feeding technologies for grow-finish swine. *Livestock science*, 129(1-3), 13-23.

813 Niemi, J.K., 2006. A dynamic programming model for optimising feeding and slaughter decisions
814 regarding fattening pigs. *Agric. Food Sci.* 15, 1-121.

815 Notes de conjoncture Aliment IFIP, 2016. Retrieved on 25 March 2020 at
816 [https://www.ifip.asso.fr/fr/content/la-note-de-conjoncture-aliment-de-l%E2%80%99ifip-](https://www.ifip.asso.fr/fr/content/la-note-de-conjoncture-aliment-de-l%E2%80%99ifip-mensuel-dinformation-sur-les-mati%C3%A8res-premi%C3%A8res)
817 [mensuel-dinformation-sur-les-mati%C3%A8res-premi%C3%A8res](https://www.ifip.asso.fr/fr/content/la-note-de-conjoncture-aliment-de-l%E2%80%99ifip-mensuel-dinformation-sur-les-mati%C3%A8res-premi%C3%A8res).

818 OECD/FAO, 2016. OECD-FAO Agricultural Outlook (Edition 2016). OECD Agriculture Statistics
819 (database). <https://doi.org/10.1787/60b7ee42-en>.

820 Peña Fernández, A., Norton, T., Youssef, A., Exadaktylos, V., Bahr, C., Bruininx, E., Vranken, E.,
821 Berckmans, D., 2019. Real-time modelling of individual weight response to feed supply for
822 fattening pigs. *Comput. Electron. Agric.* 162, 895-906.
823 <https://doi.org/10.1016/j.compag.2019.05.046>.

824 Plà-Aragones, L.M., Rodríguez-Sánchez, S.V., 2015. Optimal Delivery of Pigs to the Abattoir. In:
825 Plà-Aragones, L.M. (Ed.), Handbook of Operations Research in Agriculture and the Agri-Food
826 Industry. Springer New York, New York, NY, pp. 381-395.

827 Pomar, C., Pomar, J., Dubeau, F., Joannopoulos, E., & Dussault, J. P., 2013. The impact of daily
828 multiphase feeding on animal performance, body composition, nitrogen and phosphorus
829 excretions, and feed costs in growing-finishing pigs. *Animal*, 8(5), 704-713.

830 Pomar, C., Remus, A., 2019. Precision pig feeding: A breakthrough toward sustainability. *Anim.*
831 *Front.* 9, 52-59. <https://doi.org/10.1093/af/vfz006>.

832 Pourmoayed, R., Nielsen, L.R., Kristensen, A.R., 2016. A hierarchical Markov decision process
833 modeling feeding and marketing decisions of growing pigs. *Eur. J. Oper. Res.* 250, 925–938.
834 <https://doi.org/10.1016/j.ejor.2015.09.038>.

835 Puchinger, J., Raidl, G.R., 2005. Combining Metaheuristics and Exact Algorithms in Combinatorial
836 Optimization: A Survey and Classification, in: Mira, J., Álvarez, J.R. (Eds.), *Artificial*
837 *Intelligence and Knowledge Engineering Applications: A Bioinspired Approach*. Springer Berlin
838 Heidelberg, Berlin, Heidelberg, pp. 41-53.

839 Rodríguez-Sánchez S. V., Pla-Aragones L. M., De Castro R., 2018. Insights to optimise marketing
840 decisions on pig-grower farms. *Animal Production Science* 59, 1126-1135.

841 Teillard, F., Doyen, L., Dross, C., Jiguet, F., Tichit, M., 2017. Optimal allocations of agricultural
842 intensity reveal win-no loss solutions for food production and biodiversity. *Reg. Environ. Chang.*
843 17, 1397-1408. <https://doi.org/10.1007/s10113-016-0947-x>.

844 Van Barneveld, R. J., Hewitt, R. J. E., & D'Souza, D. N., 2018. Advances in understanding pig
845 nutritional requirements and metabolism. In *Achieving sustainable production of pig meat*
846 *Volume 2* (pp. 121-148). Burleigh Dodds Science Publishing.

847 Van Heugten, E., 2010. Growing-finishing swine nutrient recommendations and feeding
848 management. *National Swine Nutrition Guide* (ed. DJ, Meisinger), 80-95.

849 van Milgen, J., Valancogne, A., Dubois, S., Dourmad, J. Y., Sève, B., & Noblet, J., 2008. InraPorc:
850 a model and decision support tool for the nutrition of growing pigs. *Animal Feed Science and*
851 *Technology*, 143(1-4), 387-405.

852 Vautier, B., Quiniou, N., Van Milgen, J., & Brossard, L., 2013. Accounting for variability among
853 individual pigs in deterministic growth models. *Animal*, 7(8), 1265-1273.

854 Vranken, E., Berckmans, D., 2017. Precision livestock farming for pigs. *Anim. Front.* 7, 32–37.
855 <https://doi.org/10.2527/af.2017.0106>.

856 **Figure captions**

857

858 Figure 1. Diagram of the bioeconomic model and the optimization procedure. Decision variables
859 addressed are the percentage of feed A in each phase (α), live weight at the diet changes (x), target
860 weight (TW), and the maximum fattening duration (Max_d). In each iteration of the optimization
861 procedure different values for the decision variables based on CMA-ES algorithm are tested (1).
862 Feeding and shipping strategies are defined by setting values for the decision variables, (2). The
863 individual-pig growth model produces technical results for each pig on a daily basis and throughout
864 the fattening period based on the feeding and shipping strategies defined in the last stage (3). These
865 outputs are then used to calculate the economic results and environmental impacts (4). The results for
866 each individual pig are aggregated to calculate the mean gross margin per pig (the objective function)
867 (5). This procedure continues (6) until CMA-ES algorithm obtains a good-enough approximation to
868 optimum (7).

869

870 Figure 2. Digestible lysine requirement per kg of feed for growing pigs as a function of live weight
871 and overview of 2-phase feeding strategy. In each case study, 2-phase feeding strategy is defined
872 using feeds A and B. Feeds A and B had 110% and 90% of the average SID lysine requirement of
873 female pigs at 30 and 120 kg body weight (BW), respectively. Decision variables can be pig weight
874 at the diet change (x_1) and the percentages of feed A in the first (α_1) and second phases (α_2).

875

876 Figure 3. Gross margin as a function of percentage of feed A (α_1) in a blend used in a one-phase
877 feeding strategy (case study F-1: one phase with two feeds). Results are displayed with 10 or 400 pigs
878 simulated per batch and with or without variability in pig growth performance, using a step size set
879 to 0.1 for α_1 .

880

881 Figure 4. Gross margin as a function of live weight at diet change (x_1) in a two-phase feeding strategy
882 with a growing and a finishing diet (case study F-2). Results are displayed with 10 or 400 pigs
883 simulated per batch and with or without variability in pig growth performance, using a step size set
884 to 0.1 for x_1 .

885

886 Figure 5. Boxplots of gross margin as a function of the number of pigs per batch in F-2 (two phases
887 with growing and finishing diets and pig weight at the diet change as a decision variable) with 60
888 random seeds for each number of pigs. The rectangular portion of each box covers from the first up
889 to the third quartile. In order to illustrate the median, a straight line dividing the box into two equal
890 parts is drawn. Crosses indicate the mean gross margins based on 60 random seeds for each number
891 of pigs. Means that do not share a letter differ significantly according to the Tukey Honestly
892 Significant Difference test, with $\alpha = 0.05$.

893

894 Figure 6. Boxplots of the computational time as a function of the number of pigs per batch in F-2
895 based on 60 random seeds. Means that do not share a letter differ significantly according to the Tukey
896 Honestly Significant Difference test, with $\alpha = 0.05$.

897

898 Figure 7. Influence of the number of pigs per batch and the number of random seeds on the mean (M)
899 gross margin and the coefficient of variation (CV) of gross margin in F-3 (two-phase feeding strategy
900 optimizing both pig weight at diet change and the percentage of feed A in each phase).

901

902 Figure 8. Effects of pork price (low (1.173 €/kg), medium (1.314 €/kg), and high (1.662 €/kg)
903 situations), in case studies with two-phase feeding strategy, on (A) mean gross margin per pig and
904 relative benefit per pig (mean gross margin for each given case study minus mean gross margin in
905 reference R-2 (—●—)) and (B) technical outputs. Results are displayed for case studies optimizing
906 feeding (—▲—), shipping (—●—), and both strategies (---). F-3 optimizes pig weight at diet change and

percentage of feed A in both phases. S-1 optimizes shipping strategy (target weight and maximum fattening duration). FS-1 optimizes feeding (pig weight at diet change and percentage of feed A in both phases) and shipping (target weight) strategies. FS-2 optimizes feeding (pig weight at diet change and percentage of feed A in both phases) and shipping (target weight and maximum fattening duration) strategies.

912

Figure 9. Effects of pork price (low (1.173 €/kg), medium (1.314 €/kg), and high (1.662 €/kg) situations), in case studies with two-phase feeding strategy, on decision variables. Results are displayed for case studies optimizing feeding (—▲—), shipping (—●—), and both strategies (---). R-2 (—●—) simulates a reference two-phase feeding strategy. F-3 optimizes pig weight at diet change and percentage of feed A in both phases. S-1 optimizes shipping strategy (target weight and maximum fattening duration). FS-1 optimizes feeding (pig weight at diet change and percentage of feed A in both phases) and shipping (target weight) strategies. FS-2 optimizes feeding (pig weight at diet change and percentage of feed A in both phases) and shipping (target weight and maximum fattening duration) strategies.

922

Figure 10. Variations of economic (left y-axis) and environmental (right y-axis) outputs in case study FS-2. FS-2 optimizes feeding (pig weight at diet change and percentage of feed A in both phases) and shipping (target weight and maximum fattening duration) strategies. Black dashed line (---) represents the economic results. Grey lines (—) represent the environmental impacts. GM: mean gross margin per pig (objective function); CC: Climate change; AC: Acidification; EU: Eutrophication; NE: Cumulative energy demand; LO: Land occupation. All environmental impacts are expressed as a percentage of the environmental impacts obtained in the low pork price situation (1.17 €/pig) (right y-axis).

931 Table 1. Description of the decision variables of the optimization procedure.

Decision variables	Description	Unit
$X = (x_1, x_2, x_3 \dots x_{p_{m-1}})$	Where x_p is the live weight at which phase p is shifted to $p+1$	kg
$\alpha = (\alpha_1, \alpha_2, \alpha_3 \dots \alpha_{p_m})$	Where α_p is the percentage of the first feed in phase p	%
TW	Target weight	kg
Max_d	Maximum duration in the fattening unit	days

932

933 Table 2. Subscripts and superscripts used in the bioeconomic model equations.

	Description	Range of values
i	Pig	$i = \{1, \dots, I\}$
d	Day	$d = \{1, \dots, D_p\}$
p	Phase	$p = \{1, \dots, P_m\}$
g	Sex	$g = \{1: female, 2: male, 3: castrated male\}$
k	k^{th} bound of lean percentage in the payment grid	$k = \{1, \dots, k_m\}$
n	n^{th} bound of carcass weight in the payment grid	$n = \{1, \dots, n_m\}$

934

935 Table 3. Abbreviations and description of the bioeconomic model inputs.

Abbreviation	Description	Unit
$z_{p,1}$	Price of the first feed in phase p	€/t
$z_{p,2}$	Price of the second feed in phase p	€/t
PP	Piglet price (weight: 25 kg)	€/piglet
ILW^{ig}	Initial live weight of pig i of sex g	kg

936

937 Table 4. Quantities used in the bioeconomic model.

Notation	Description	Unit
LW_d^{ig}	Live weight of pig i of sex g on day d	kg
q_d^{ig}	Feed intake of pig i of sex g on day d	kg
$FC^{ig}(X, \alpha, TW, Max_d)$	Feeding cost of pig i of sex g	€
$SLP^{ig}(X, \alpha, TW, Max_d)$	Selling price of pig i of sex g	€/kg carcass weight
$D_p^{ig}(X)$	Vector of days belonging to phase p of pig i of sex g	day
$FSP^{ig}(X, \alpha, TW, Max_d)$	Final selling price of pig i of sex g	€
$GM^{ig}(X, \alpha, TW, Max_d)$	Gross margin of pig i of sex g	€
$ADP^{ig}(ILW^i)$	Additional price of piglet i of sex g	€
PGC^{ig}	Cost of piglet i of sex g	€

938

939 Table 5. Description of the four sets of analyses including objective, number of pigs per batch and
 940 seeds, and types of case studies used.

Set of analyses	Objective	Types of case studies	Number of simulated pigs per batch and number of seeds
1	Explore the behavior of the optimization procedure	R ¹	10 and 400 pigs
2	Define recommendation of use of the optimization procedure	F	From 10 to 400 pigs with 60 random seeds
3	Explore some practical questions	R, F, S, and FS	200 pigs with 20 seeds
4	Explore effects of pork price	F, S and FS	200 pigs with 20 seeds

941 ¹ Case studies simulated with one decision variable varying from lower to upper bound.
 942 R: reference strategy simulated, F: Feeding strategy optimized, S: Shipping strategy optimized, FS: Feeding
 943 and shipping strategies simultaneously optimized

944 Table 6. Description of the simulated and optimized case studies, indicating the decision variables (D) and their bounds during optimization. Asterisks
 945 indicate when they are considered as input parameters.

	Case studies									
	Simulated		Optimized						Bounds	
	R-1	R-2	F-1	F-2	F-3	S-1	FS-1	FS-2	Min	Max
Percentage of feed A in each phase (α_1, α_2)	$\alpha_1 = 100^*$	(100*, 55*)	D	(100*, 55*)	D	(100*, 55*)	D	D	0	100
Live weight at the diet change (x_1 , kg)	-	65*	-	D	D	65*	D	D	30	120
Target weight (TW , kg)	116.4*	116.4*	116.4*	116.4*	116.4*	D	D	D	110	130
Maximum fattening duration (Max_d , day)	108*	108*	108*	108*	108*	D	108*	D	100	125

946 R: reference strategy simulated, F: Feeding strategy optimized, S: Shipping strategy optimized, FS: Feeding and shipping strategies simultaneously optimized

947 Table 7. Mean (± 1 standard deviation) of gross margin, decision variables, and technical outputs obtained in the simulation and optimization case
948 studies, run with 20 random seeds and 200 pigs per batch in the third set of analyses. Bold text indicates decision variables in each case study.

Case studies	Gross margin (€/pig)	LW at the diet change (kg) (x_1)	% of feed A in phase 1 (α_1)	% of feed A in phase 2 (α_2)	Target weight (kg) (TW)	Maximum fattening duration (days) (Max_d)	Computational time (min)	Slaughter weight (kg)	Feed cost (€/pig)
R-1	25.26 ^{e*} \pm 0.86	-	100	-	116.4	108	-	116.13 ^c \pm 0.51	47.91 ^b \pm 0.18
F-1	29.28 ^c \pm 0.80	-	49.11 \pm 4.04	-	116.4	108	14.99 ^c \pm 3.73	115.30 ^d \pm 0.60	42.49 ^g \pm 0.17
R-2	28.37 ^d \pm 0.81	65	100	54.65	116.4	108	-	115.79 ^{c,d} \pm 0.46	44.44 ^d \pm 0.15
F-2	29.30 ^c \pm 0.82	38.26^c \pm 4.04	100	54.65	116.4	108	11.37 ^c \pm 3.24	115.69 ^{c,d} \pm 0.56	43.22 ^f \pm 0.19
F-3	29.78 ^{b,c} \pm 0.73	54.17^{a,b} \pm 2.84	69.51 \pm 4.48	42.08 \pm 3.41	116.4	108	24.27 ^b \pm 5.73	115.43 ^d \pm 0.36	42.45 ^e \pm 0.17
S-1	29.69 ^{b,c} \pm 0.89	65	100	54.65	124.27^c \pm 0.52	114.73^a \pm 2.06	13.33 ^c \pm 3.37	121.13 ^a \pm 0.57	48.16 ^a \pm 0.17
FS-1	30.31 ^b \pm 0.84	52.97^b \pm 2.44	72.81 \pm 3.34	46.83 \pm 2.20	124.92^b \pm 0.87	108	26.25 ^b \pm 5.89	117.00 ^b \pm 0.68	43.47 ^e \pm 0.21
FS-2	31.26 ^a \pm 0.84	55.70^a \pm 2.73	71.41 \pm 4.67	40.22 \pm 2.68	125.48^a \pm 0.42	113.65^a \pm 1.32	51.79 ^a \pm 6.38	120.73 ^a \pm 0.71	46.02 ^c \pm 0.17

949 *Means that do not share a letter differ significantly according to the Tukey Honestly Significant Difference test, with $\alpha = 0.05$

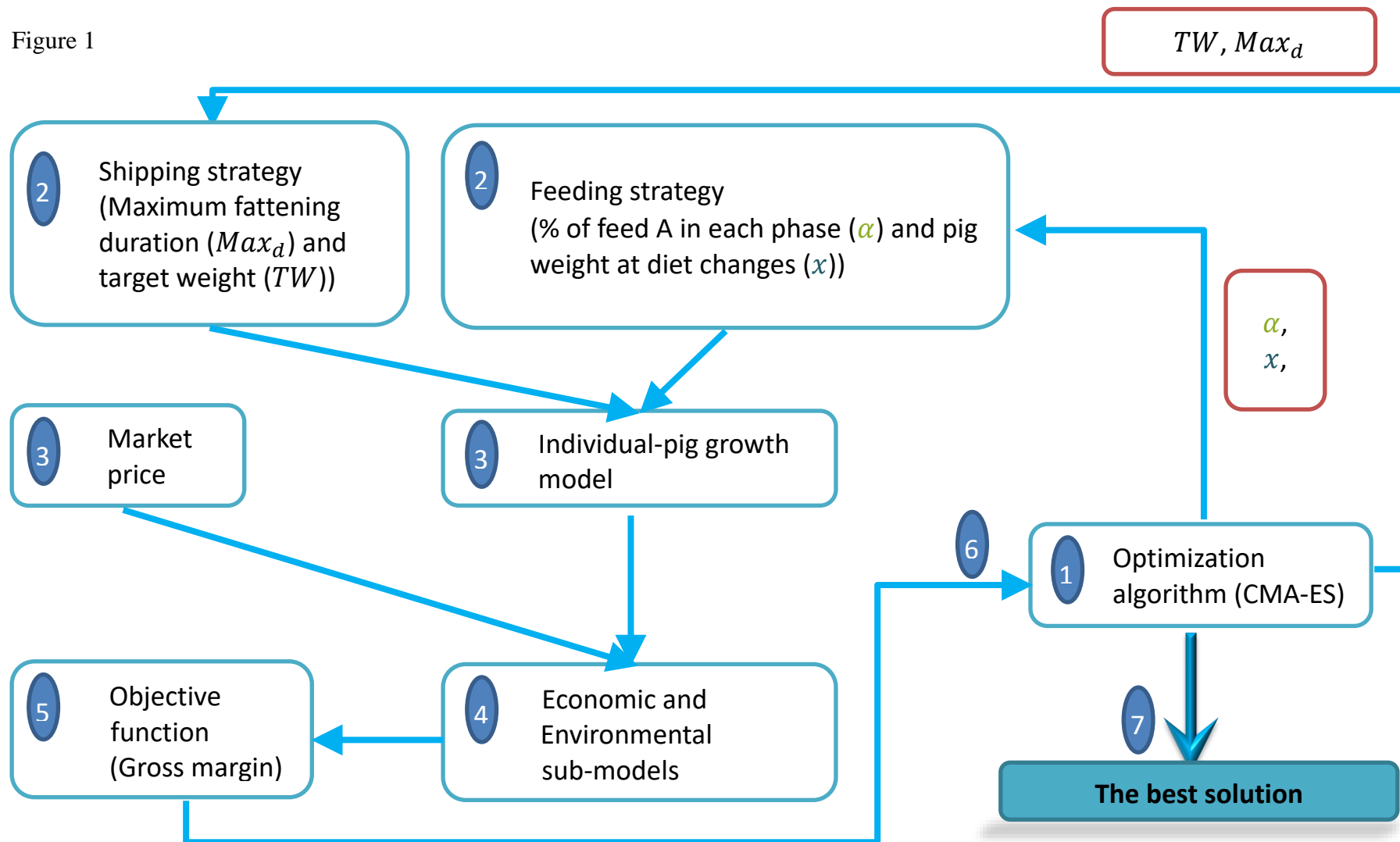
950 LW = live weight

951 Table 8. Mean (± 1 standard deviation) of environmental impacts per kg live weight gain obtained in
 952 the simulation and optimization case studies, run with 20 random seeds and 200 pigs per batch in the
 953 third set of analyses.

Case studies	Climate change (kg CO ₂ -eq.)	Acidification (g SO ₂ -eq.)	Eutrophication (g PO ₄ -eq.)	Cumulative energy demand (MJ)	Land occupation (m ² year)
R-1	2.19 ^{a*} \pm 0.02	56.51 ^a \pm 0.67	19.11 ^a \pm 0.21	13.88 ^a \pm 0.10	3.72 ^f \pm 0.03
F-1	2.02 ^{d,e} \pm 0.01	49.13 ^e \pm 0.47	16.93 ^f \pm 0.03	12.02 ^{f,g} \pm 0.08	3.84 ^{b,c} \pm 0.03
R-2	2.07 ^c \pm 0.02	51.55 ^c \pm 0.53	17.63 ^c \pm 0.17	12.70 ^c \pm 0.08	3.76 ^e \pm 0.03
F-2	2.03 ^d \pm 0.02	49.83 ^d \pm 0.56	17.12 ^e \pm 0.18	12.26 ^d \pm 0.09	3.79 ^{d,e} \pm 0.03
F-3	2.01 ^e \pm 0.01	48.93 ^e \pm 0.42	16.87 ^f \pm 0.13	11.98 ^g \pm 0.08	3.84 ^{b,c} \pm 0.03
S-1	2.11 ^b \pm 0.02	52.97 ^b \pm 0.61	18.09 ^b \pm 0.19	12.90 ^b \pm 0.09	3.85 ^b \pm 0.03
FS-1	2.02 ^{d,e} \pm 0.01	49.23 ^e \pm 0.48	16.95 ^f \pm 0.15	12.09 ^f \pm 0.08	3.82 ^{c,d} \pm 0.03
FS-2	2.06 ^c \pm 0.01	50.32 ^d \pm 0.46	17.32 ^d \pm 0.15	12.17 ^e \pm 0.06	3.94 ^a \pm 0.04

954 *Means that do not share a letter differ significantly according to the Tukey Honestly Significant Difference
 955 test, with $\alpha = 0.05$

Figure 1



2-phase feeding strategy (a blend of feeds A and B)

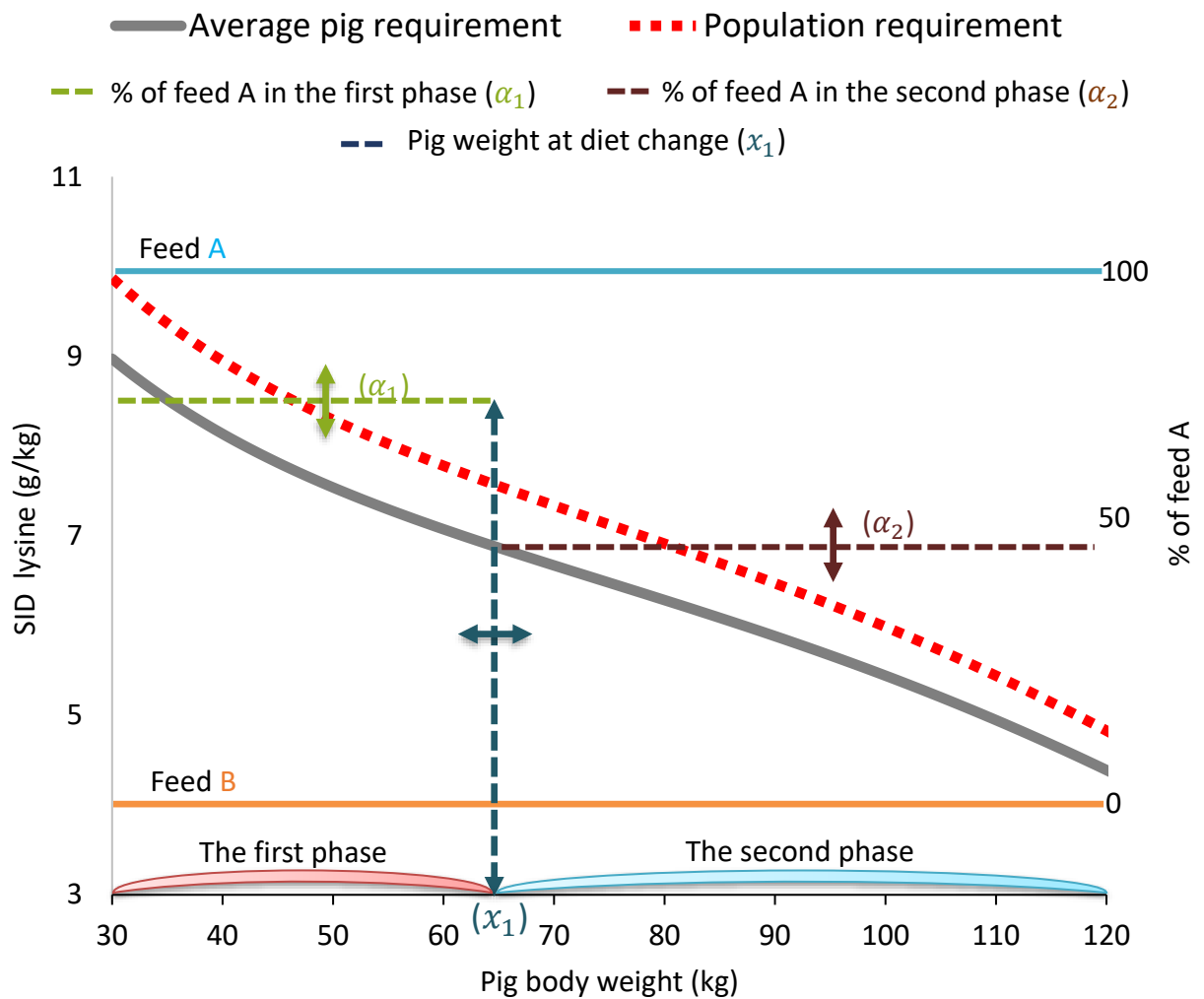


Figure 2

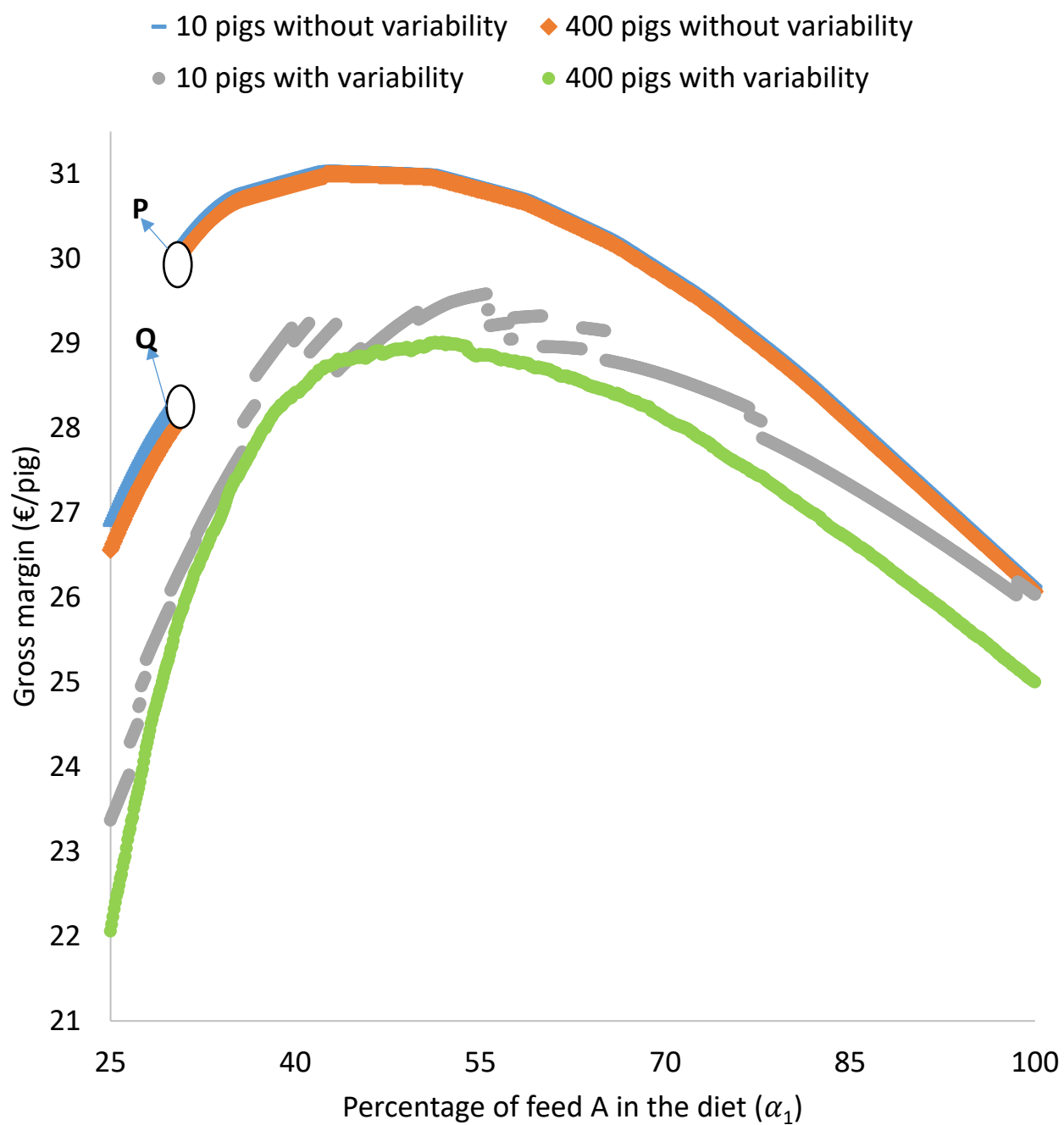


Figure 3

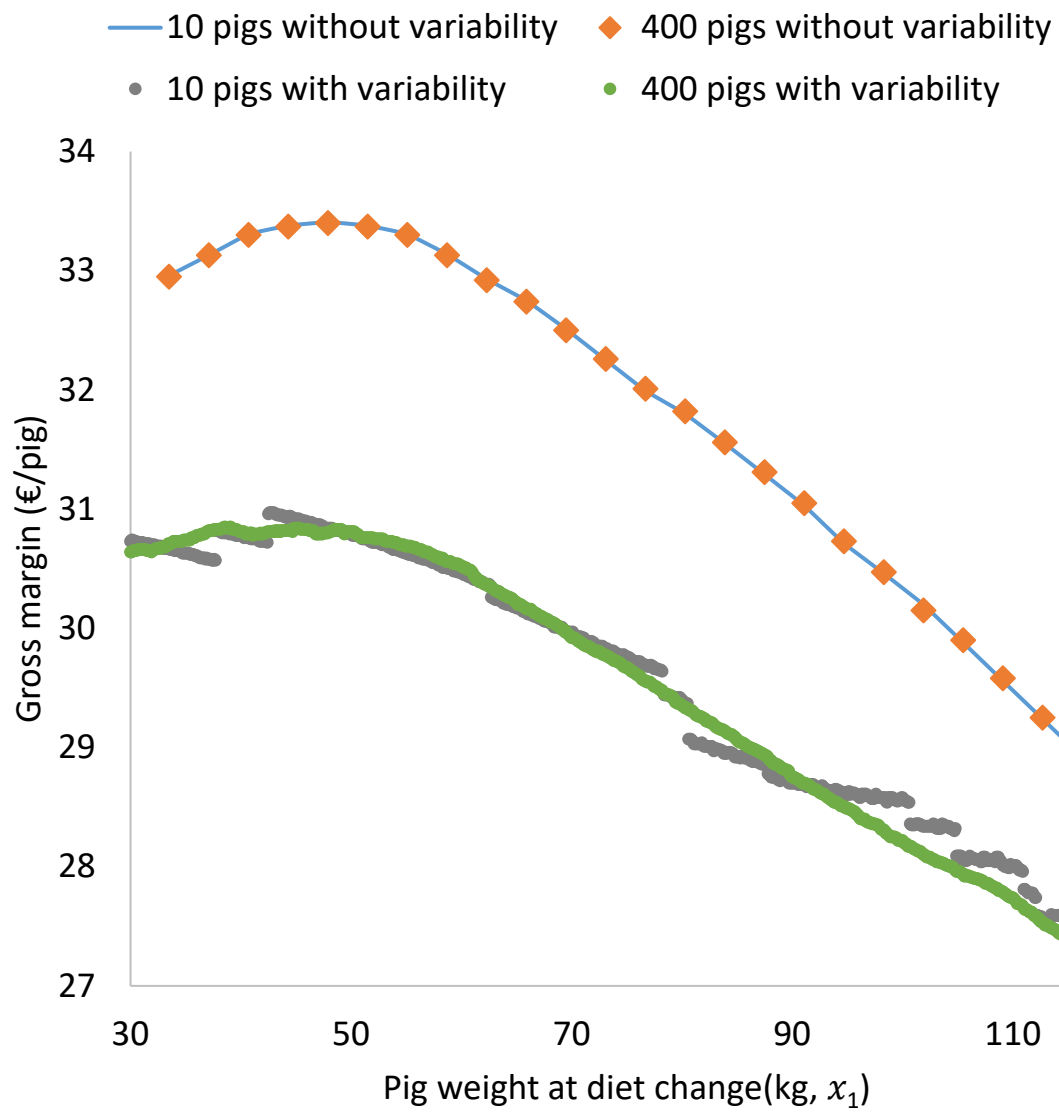


Figure 4

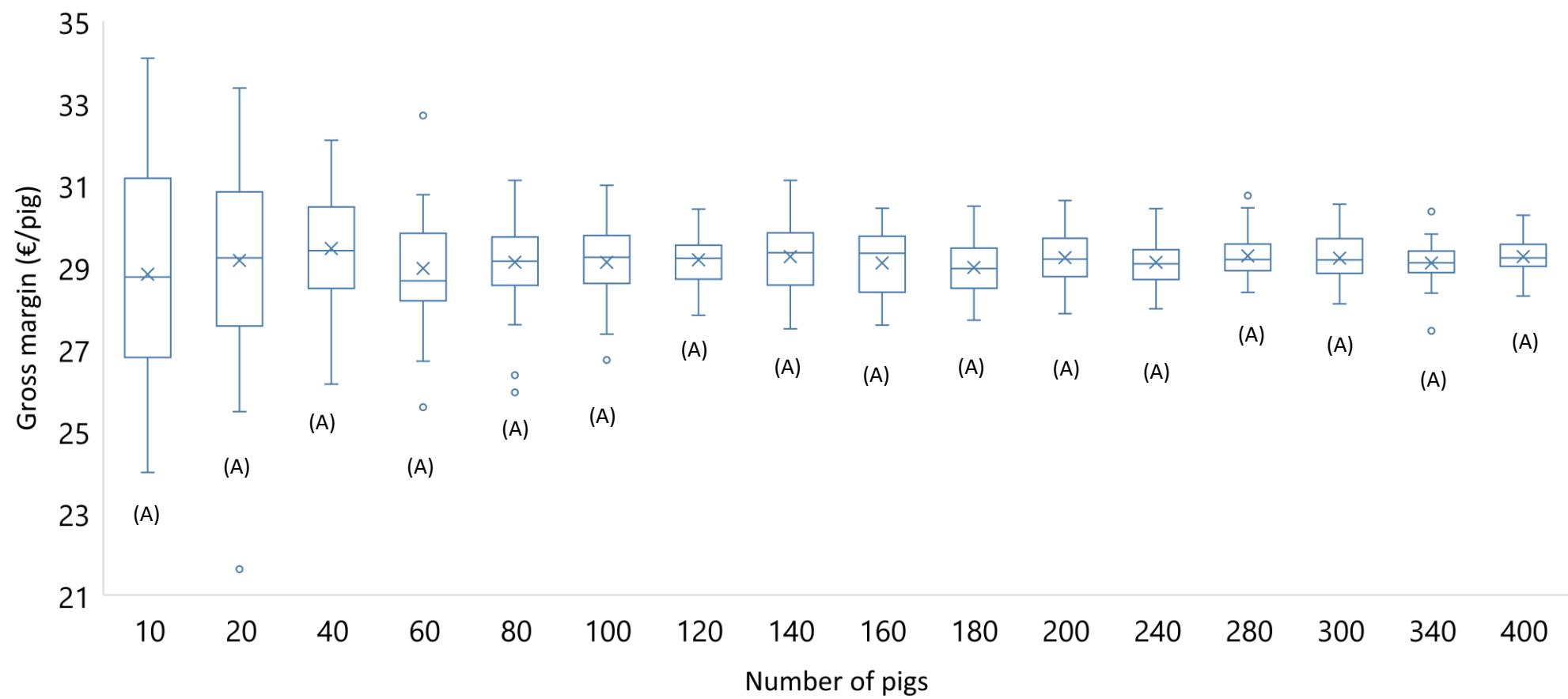


Figure 5

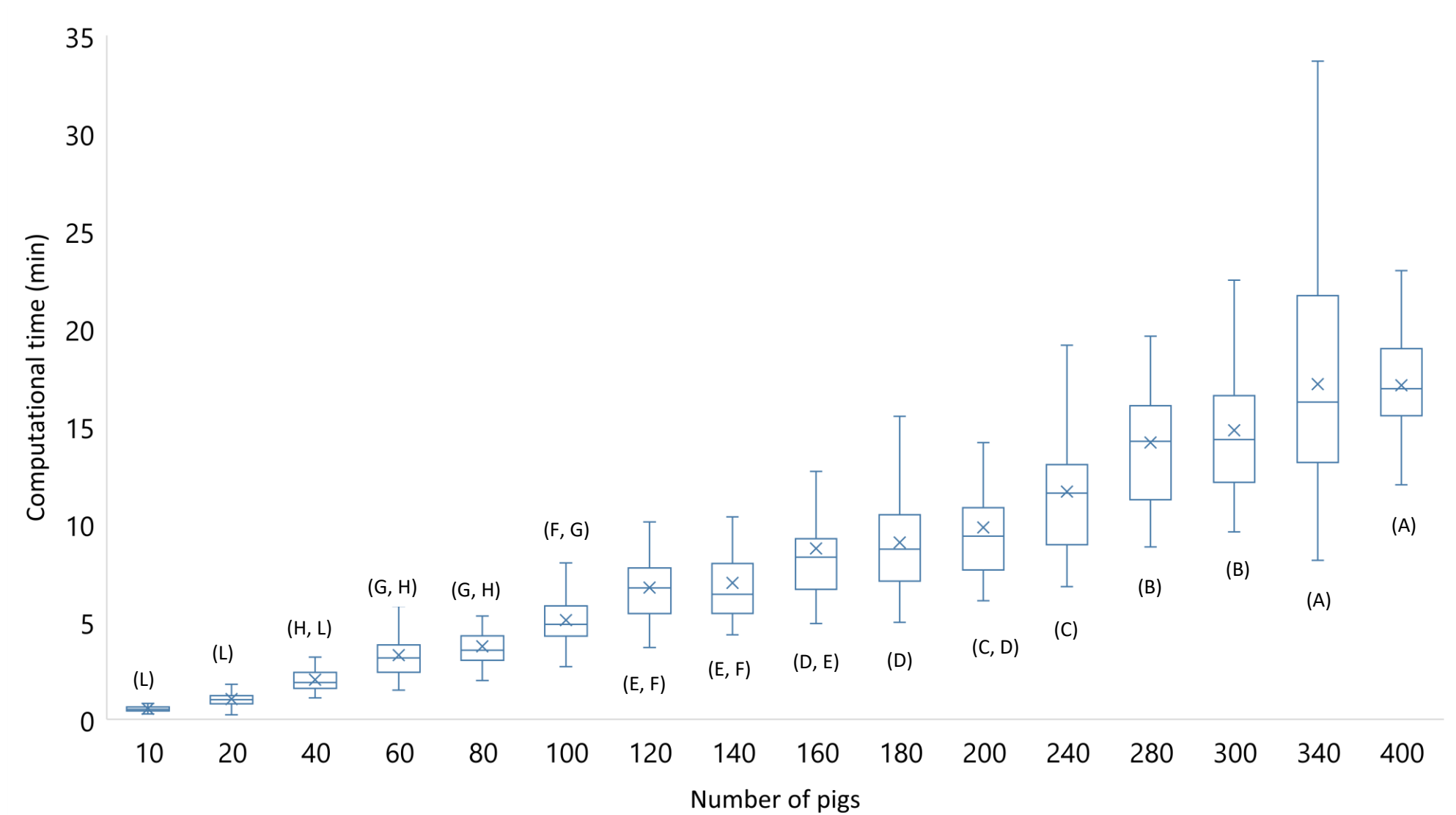


Figure 6

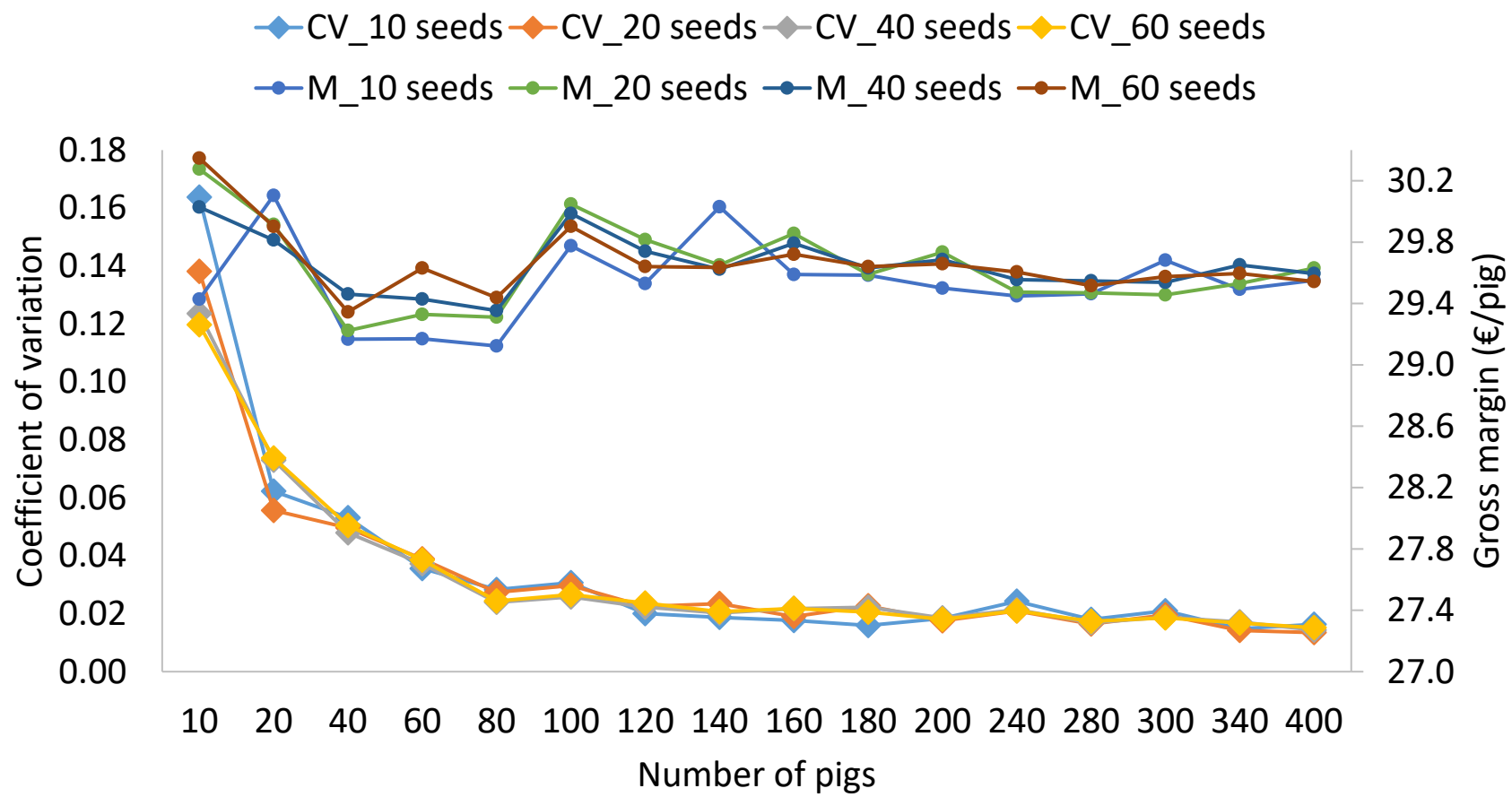


Figure 7

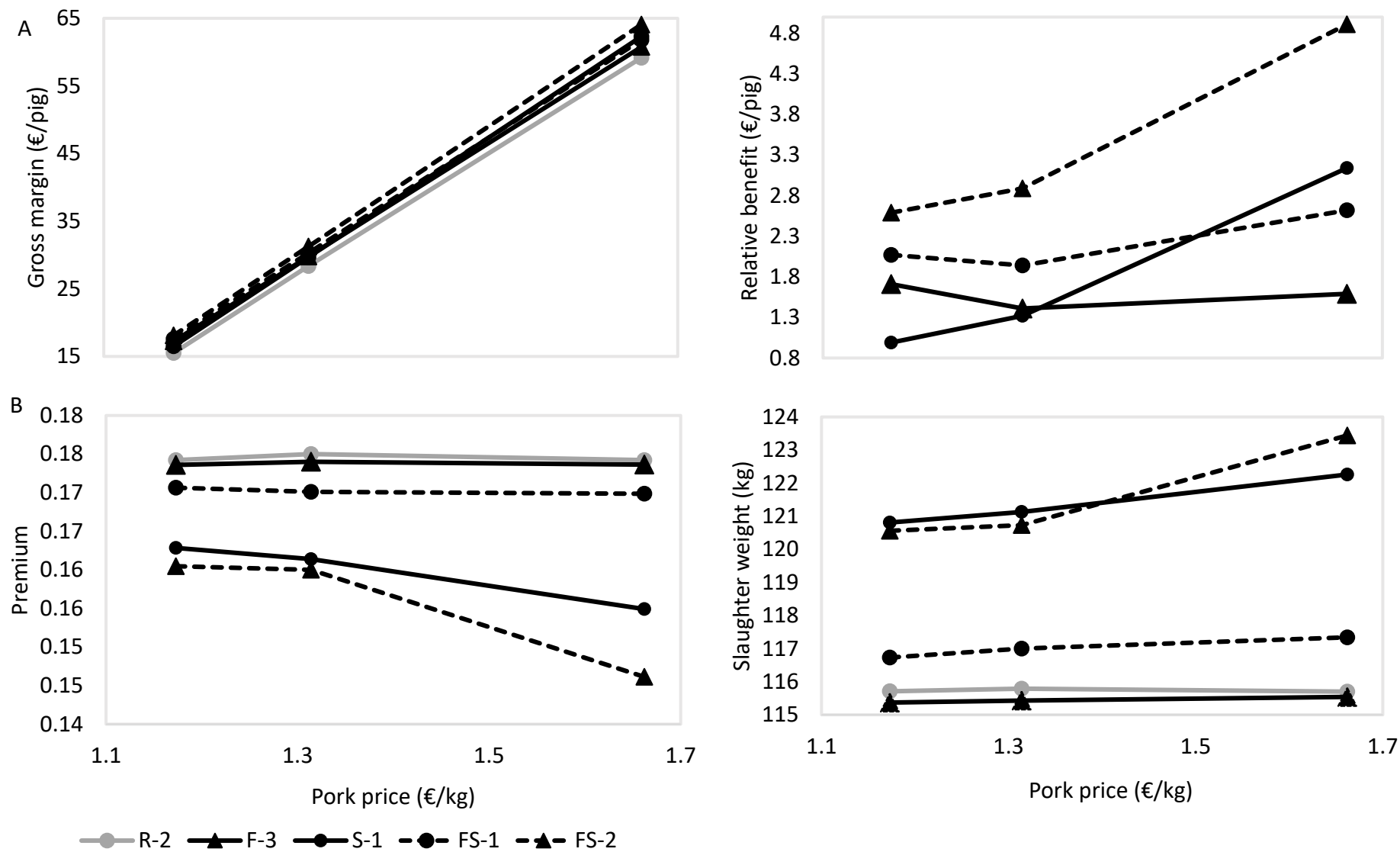


Figure 8

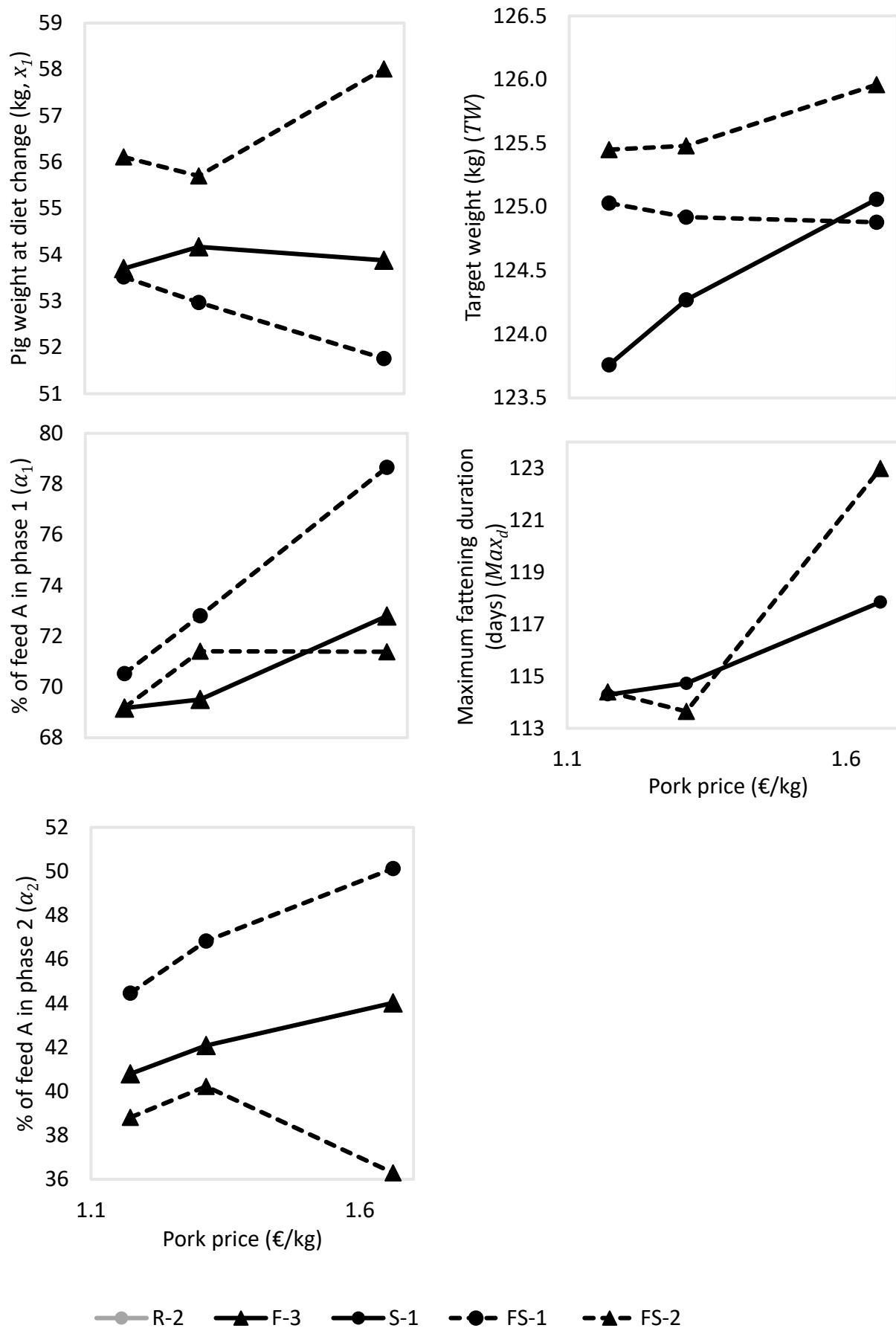


Figure 9

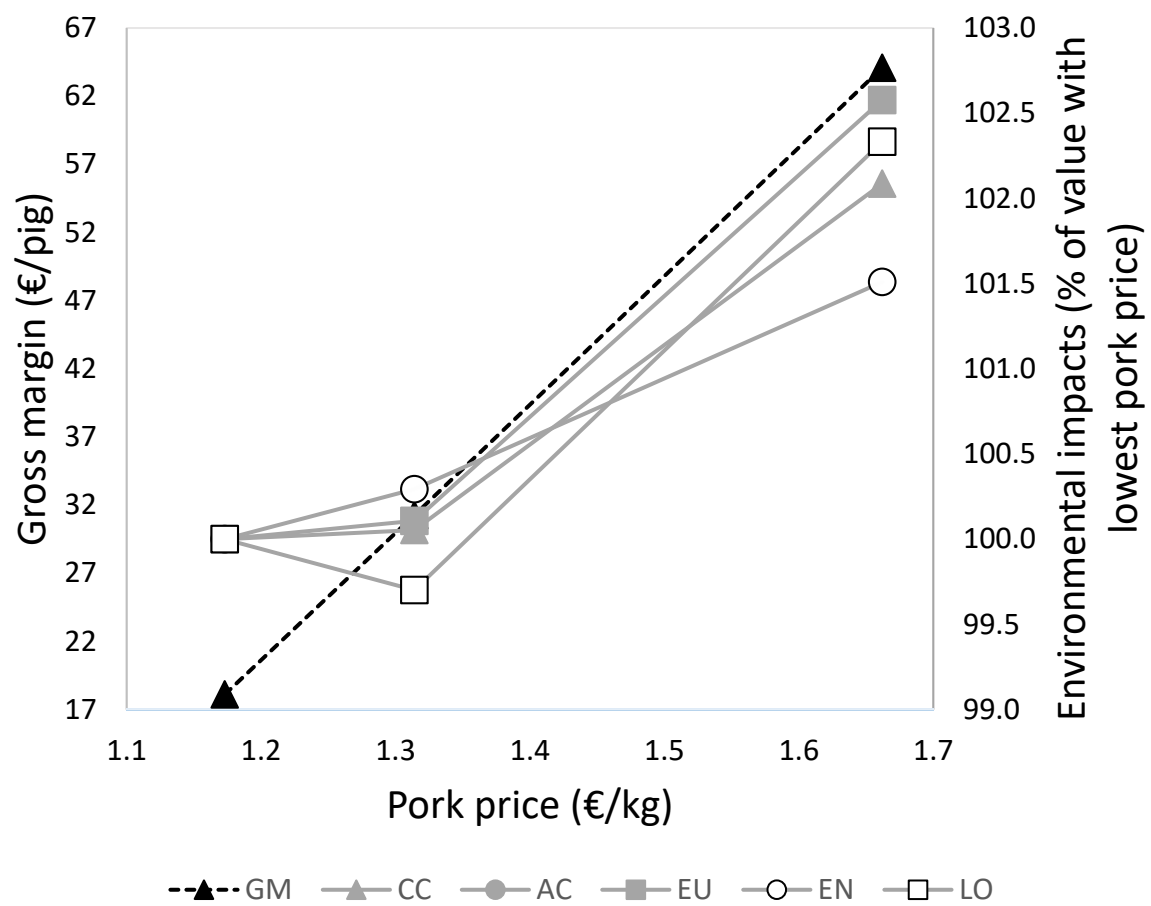


Figure 10