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

3

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9 algorithm, Market price.

10

11 **ABSTRACT**

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

27 strategies improved the mean gross margin per pig by 4.7%. Optimizing both feeding and shipping  
28 strategies improved the gross margin per fattened pig by 10% (2.88 €/pig, with medium pork price  
29 (1.314€/kg)) compared to the common practice on farms in France. Pork price had a limited effect on  
30 feeding decisions when optimized alone, but a strong impact on shipping decisions. Economic  
31 optimization of pig fattening inconsistently affected the environmental impacts. However, increasing  
32 pork price improved the optimized mean gross margin per pig but increased all environmental  
33 impacts. To our knowledge, this is the first tool able to optimize both feeding and shipping strategies  
34 while considering effects of variability in growth potential among a batch of pigs. These features  
35 allow consideration of the interaction effect of feeding and shipping strategies on the economic  
36 outputs of the batch, and investigation of the trade-off between production cost and technical  
37 performance. This tool should interest the pig sector since it can identify the best feeding and shipping  
38 strategies depending on the economic context. Further work should consider multiobjective  
39 optimization with both economic and environmental objectives.

40

## 41 **1. Introduction**

42 The world population is expected to reach 9.8 billion by 2050, an increase of 20 percent from today  
43 (FAO, 2017). Coupled with an improving standard of living in developing countries, this will increase  
44 demand for animal products by 50% (FAO, 2017). The expected growth in animal production raises  
45 many concerns about its short and long-term effects. Pork is the most consumed meat in the world. It  
46 accounts for 39% of the world's meat intake in 2015 (OECD/FAO, 2016) and its demand is increasing  
47 (+37% expected over the period 2010-2050).

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

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

55 The pig-fattening unit, which is the main contributor to environmental impacts of pig production,  
56 represents the majority of pig production costs (Pomar and Remus, 2019) and its profitability depends  
57 largely on market prices of pig carcasses and feed ingredients (Pourmoayed et al., 2016; AHDB,  
58 2018). Farmers receive revenue from delivering pigs to the slaughterhouse when pigs reach a  
59 marketable weight or when the fattening room must be emptied in the “All-in All-out” management  
60 system (Plà-Aragones and Rodríguez-Sánchez, 2015). In most European countries, the revenue from  
61 each pig depends on carcass weight and carcass leanness, which are assessed by a payment grid.  
62 Carcass weight resulting in a premium or a discount (per kg of carcass weight) is achieved at a  
63 different fattening duration for each pig in the batch. This is due to variability in feed intake and  
64 potential for body protein deposition among pigs. Feeding costs depend on the price of feeds and the  
65 total consumption of each pig, which also varies among pigs and depends on the ability of the feeding  
66 strategy to meet the pigs’ nutritional requirements. In practice, for a given pig, extending the fattening  
67 duration increases both carcass weight and feeding costs but decreases carcass leanness. Depending  
68 on each pig’s potential, the feeding strategy, and the market price, extending fattening duration may  
69 decrease or increase the gross margin (Leen et al., 2018). In the meantime, extending the fattening  
70 duration increases environmental impacts. The gross margin per pig, feeding costs and environmental  
71 impacts can thus vary considerably depending on the feeding program. Therefore, interactions  
72 between feeding programs, the delivery of pigs to the slaughterhouse, and the variability in pig growth  
73 performance largely determine the profitability of the pig-fattening unit and the consequences of the  
74 production on the environment; however, they are difficult to predict. The purpose of this study was  
75 to account for these interactions when optimizing the economic output of a batch of pigs.

76 The scientific community has focused on the nutritional requirements of growing pigs for energy and  
77 amino acids (van Milgen et al., 2008; Van Barneveld et al., 2018). Nutritional requirements vary  
78 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

181  
182 The model developed by Cadero et al. (2018a) is a simulation model, which is not able to find optimal  
183 feeding and shipping strategies in different economic contexts. Consequently, the present study  
184 developed an optimization procedure that overcomes this missing feature, maximizes the economic  
185 performance of a batch of pigs, and identifies the best feeding and shipping strategies in a given  
186 economic context.

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

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

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

- 195 - 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  
196 pig live weight at which phase  $p$  is shifted to phase  $p+1$
- 197 - Percentage of feed A in each phase  $p$ ,  $\alpha = (\alpha_1, \alpha_2, \alpha_3 \dots \alpha_{p_m})$ , where  $\alpha_p$  is the percentage of  
198 feed A in a blend used during phase  $p$
- 199 - Target slaughter weight  $TW$ , which is the minimum live weight of a pig ready for slaughter. Pigs  
200 that have reached the target weight are selected for shipment to the slaughterhouse (individual  
201 marketing). Pigs that have not yet reached the target weight are kept until the next shipment,  
202 unless the maximum fattening duration has been reached.
- 203 - Maximum fattening duration ( $Max_d$ ) which is the maximum allowed duration including cleaning  
204 and disinfecting time before the arrival of a new batch of pigs. When the maximum fattening  
205 duration is reached, all remaining pigs are sent to the slaughterhouse in the next shipment. Light

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

### 208 2.3. Mathematical formulation of the bioeconomic model

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

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

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

220 The feeding cost of pig  $i$  of sex  $g$  results from the cost associated with the consumption of feeds A  
 221 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:

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

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

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

222 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  
 223 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

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

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

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

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

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

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

#### 245 *2.4. Optimization approach*

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

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

261 In order to model problems in pig farming systems, non-exact optimization algorithms have already  
262 been used (Morel et al., 2012; Lehmann et al., 2013; Britz and Kallrath, 2012; Accatino et al., 2019;  
263 Teillard et al., 2016; Groot et al., 2010; Groot and Rossing, 2011; Alexander et al., 2006). Among  
264 different evolutionary algorithms, the covariance matrix adaptation evolution strategy (CMA-ES)  
265 was chosen due to its ability to reach an excellent performance on the accuracy, its efficiency, and  
266 faster computing speed to deal with non-convex problems compared to other approaches (Hansen,  
267 2006; Hansen and Kern, 2010). CMA-ES belongs to the family of genetic algorithms (Holland, 1973).  
268 In CMA-ES, the multivariate normal distribution used to sample potential solutions is used as the  
269 mutation operator, and a covariance matrix is used to reach regions with expected lower objective  
270 values. Therefore, any result obtained from CMA-ES is a pseudo-optimum or a good-enough  
271 approximation to the optimum as CMA-ES is a non-exact optimization method. The model is  
272 available open access on the Datainrae data warehouse (<https://doi.org/10.15454/OWJJUU>).

273 *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.

299 - Reference two-phase R-2, in which a two-phase feeding strategy was simulated with Growing  
300 (G) and Finishing (F) diets based on feeds A and B. Diet G (feed A only) was fed in the first  
301 phase from 70 days of age until a mean BW of 65 kg. In the second phase, diet F, supplied  
302 from 65 kg BW to the end of the fattening period, provided 0.76 g SID lysine/MJ NE,  
303 corresponding to 110% of the mean requirement at 65 kg BW. Diet F was obtained by mixing  
304 54.7% of feed A and 45.3% of feed B (Figure 2). This case study corresponds to a typical two-  
305 phase feeding strategy used in practice in France (AGRESTE, 2008).

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

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

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

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

338 *Parameterization of the optimization procedure.* All case studies that included the same decision  
339 variables used the same initial points for the CMA-ES algorithm: 50 kg for live weight at the diet  
340 change ( $x_1$ ), 80% of feed A in the first and second phases ( $\alpha_1, \alpha_2$ ), 120 kg for target weight ( $TW$ ),  
341 and 108 days for the maximum fattening duration ( $Max_d$ ). The criterion for stopping the iterations  
342 was the function tolerance. Iterations end when the range of the values of the best objective function  
343 of the last  $10+4n$  ( $n$  is the number of decision variables) generations and all function values of the  
344 current generation are lower than the function tolerance. The default value of the CMA-ES algorithm  
345 ( $10^{-12}$ ) was used for the results presented below. However, due to the limitation of function values to  
346 the second digit after the decimal point, the shape of the function, and the averaging performed for  
347 different choices of a set of pig profiles (different seeds of the pseudo random draw of the profiles),  
348 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 m<sup>2</sup> year in F-1 vs. 3.72 m<sup>2</sup> 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**

478 (1.314€/kg), environmental impacts remained stable relatively to the low pork price situation (1.173  
479 €/kg) while gross margin increased by 18%. With high pork price (1.662 €/kg), all environmental  
480 impacts increased compared to those in low pork price (1.173 €/kg) situation, by 1.5% to 2.7%:  
481 climate change (2.1%), acidification (2.7%), eutrophication (2.6%), cumulative energy demand  
482 (1.5%), and land occupation (2.3%).

483

#### 484 **4. Discussion**

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

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

503 *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

556 (10 pigs) was 55.5%, whereas the optimal percentage of feed A was 51% at the batch level (400 pigs).  
557 In Figure 4, the optimal pig weight at the diet change was 43 kg at the pen level (10 pigs), whereas  
558 the optimal pig weight at the diet change at the batch level (400 pigs) was 38 kg. Since the optimal  
559 strategies at the pen level differed from those observed at the batch level, ignoring variability between  
560 pens might change optimal feeding and shipping strategies and consequently reduce the profitability  
561 of a batch of pigs.

#### 562 *4.2 Application of the optimization procedure*

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

#### 581 *4.3 Optimization of feeding and shipping strategies*



582 Results of the third set of analyses highlighted that the economic optimum differs from the technical  
583 optimum. This is consistent with other studies observing that maximizing profitability differs from  
584 maximizing growth performance, and implies not meeting the nutrient requirements of all pigs  
585 (Chiba, 2000; Van Heugten, 2010; Niemi et al., 2010; Pomar and Remus, 2019). R-2 supplied 110%  
586 of the mean population requirement in digestible lysine at the start of each phase. This level of lysine  
587 meets the requirements of most pigs to express their growth potential, regardless of the economic  
588 aspects (Brossard et al., 2009). Optimizing the feeding strategy (F-3); however, decreased the  
589 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  
590 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.  
591 It increased slaughter age and decreased average daily gain, slaughter weight, and lean percentage.  
592 Consequently, feed cost (€/pig) in F-3 was lower than that in R-2. Indeed, satisfying the need of all  
593 pigs requires supplying more feed A (rich diet), which is more expensive than feed B (poor diet).  
594 These results highlight the trade-off between feed cost and technical performance in the optimization  
595 procedure.

596 When optimizing the target weight in addition to the feeding strategy (FS-1), target weight increased  
597 and gross margin per fattened pig improved by 6.84% compared to R-2. However, slaughter weight  
598 increased only for fast-growing pigs. Slow-growing pigs were delivered to the slaughterhouse at the  
599 end of the fattening duration and resulted in a discount. By optimizing target weight and the maximum  
600 fattening duration (FS-2 and S-1), the mean gross margin per pig improved, which is consistent with  
601 the results of Leen et al. (2018). This result may be explained by increased slaughter weight and  
602 premiums of slow-growing pigs. In the economic context used, extending the fattening duration (FS-  
603 2) had a better outcome for the total gross margin per batch. However, the maximum fattening  
604 duration is a decision variable, which should be considered with care. On most farrow-to-finish farms,  
605 the maximum fattening duration is rather a constraint related to the number of rooms and the batch  
606 management system. This means that when performing the optimization, if modifying the maximum  
607 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*

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

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

#### 653 *4.5 Environmental impacts*

654 Since balancing economic outputs and the environmental impacts is a big challenge for pig  
655 production, we examined the effect of economic optimization of pig-fattening on the environment  
656 burden. When optimizing only the feeding strategy, global warming potential and eutrophication  
657 decreased, but land occupation increased. These reductions in environmental impacts may be  
658 explained by decreasing the amount of feed A (high nutrient density), which is consistent with the  
659 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

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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

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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 ( $\alpha$ ), 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 ( $\alpha_1$ ) and second phases ( $\alpha_2$ ).

875

876 Figure 3. Gross margin as a function of percentage of feed A ( $\alpha_1$ ) 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  $\alpha_1$ .

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

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

912

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

922

923 Figure 10. Variations of economic (left y-axis) and environmental (right y-axis) outputs in case study  
924 FS-2. FS-2 optimizes feeding (pig weight at diet change and percentage of feed A in both phases) and  
925 shipping (target weight and maximum fattening duration) strategies. Black dashed line ( --- )  
926 represents the economic results. Grey lines ( — ) represent the environmental impacts. GM: mean  
927 gross margin per pig (objective function); CC: Climate change; AC: Acidification; EU:  
928 Eutrophication; NE: Cumulative energy demand; LO: Land occupation. All environmental impacts  
929 are expressed as a percentage of the environmental impacts obtained in the low pork price situation  
930 (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 $\alpha_p$ 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
$ILW^{i_g}$	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 <sup>1</sup>	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 <sup>1</sup> 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 ( $\alpha_1, \alpha_2$ )	$\alpha_1 = 100^*$	(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 ( $\pm 1$  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 ( $\alpha_1$ )	% of feed A in phase 2 ( $\alpha_2$ )	Target weight (kg) ( $TW$ )	Maximum fattening duration (days) ( $Max_d$ )	Computational time (min)	Slaughter weight (kg)	Feed cost (€/pig)
R-1	25.26 <sup>e*</sup> $\pm$ 0.86	-	100	-	116.4	108	-	116.13 <sup>c</sup> $\pm$ 0.51	47.91 <sup>b</sup> $\pm$ 0.18
F-1	29.28 <sup>c</sup> $\pm$ 0.80	-	<b>49.11 <math>\pm</math> 4.04</b>	-	116.4	108	14.99 <sup>c</sup> $\pm$ 3.73	115.30 <sup>d</sup> $\pm$ 0.60	42.49 <sup>g</sup> $\pm$ 0.17
R-2	28.37 <sup>d</sup> $\pm$ 0.81	65	100	54.65	116.4	108	-	115.79 <sup>c,d</sup> $\pm$ 0.46	44.44 <sup>d</sup> $\pm$ 0.15
F-2	29.30 <sup>c</sup> $\pm$ 0.82	<b>38.26<sup>c</sup> <math>\pm</math> 4.04</b>	100	54.65	116.4	108	11.37 <sup>c</sup> $\pm$ 3.24	115.69 <sup>c,d</sup> $\pm$ 0.56	43.22 <sup>f</sup> $\pm$ 0.19
F-3	29.78 <sup>b,c</sup> $\pm$ 0.73	<b>54.17<sup>a,b</sup> <math>\pm</math> 2.84</b>	<b>69.51 <math>\pm</math> 4.48</b>	<b>42.08 <math>\pm</math> 3.41</b>	116.4	108	24.27 <sup>b</sup> $\pm$ 5.73	115.43 <sup>d</sup> $\pm$ 0.36	42.45 <sup>g</sup> $\pm$ 0.17
S-1	29.69 <sup>b,c</sup> $\pm$ 0.89	65	100	54.65	<b>124.27<sup>c</sup> <math>\pm</math> 0.52</b>	<b>114.73<sup>a</sup> <math>\pm</math> 2.06</b>	13.33 <sup>c</sup> $\pm$ 3.37	121.13 <sup>a</sup> $\pm$ 0.57	48.16 <sup>a</sup> $\pm$ 0.17
FS-1	30.31 <sup>b</sup> $\pm$ 0.84	<b>52.97<sup>b</sup> <math>\pm</math> 2.44</b>	<b>72.81 <math>\pm</math> 3.34</b>	<b>46.83 <math>\pm</math> 2.20</b>	<b>124.92<sup>b</sup> <math>\pm</math> 0.87</b>	108	26.25 <sup>b</sup> $\pm$ 5.89	117.00 <sup>b</sup> $\pm$ 0.68	43.47 <sup>e</sup> $\pm$ 0.21
FS-2	31.26 <sup>a</sup> $\pm$ 0.84	<b>55.70<sup>a</sup> <math>\pm</math> 2.73</b>	<b>71.41 <math>\pm</math> 4.67</b>	<b>40.22 <math>\pm</math> 2.68</b>	<b>125.48<sup>a</sup> <math>\pm</math> 0.42</b>	<b>113.65<sup>a</sup> <math>\pm</math> 1.32</b>	51.79 <sup>a</sup> $\pm$ 6.38	120.73 <sup>a</sup> $\pm$ 0.71	46.02 <sup>c</sup> $\pm$ 0.17

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

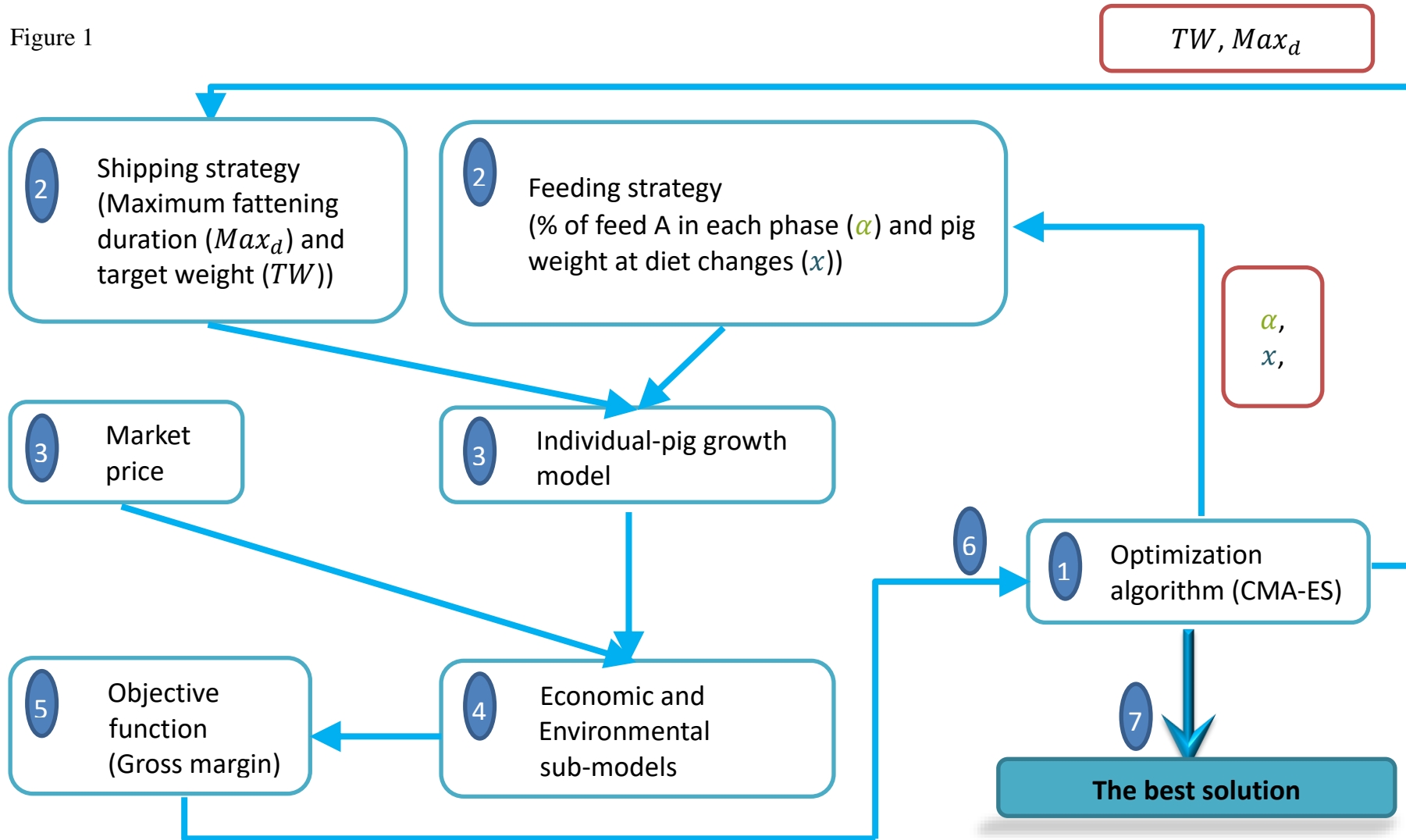
950 LW = live weight

951 Table 8. Mean ( $\pm 1$  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 <sub>2</sub> -eq.)	Acidification (g SO <sub>2</sub> -eq.)	Eutrophication (g PO <sub>4</sub> -eq.)	Cumulative energy demand (MJ)	Land occupation (m <sup>2</sup> year)
R-1	2.19 <sup>a*</sup> $\pm$ 0.02	56.51 <sup>a</sup> $\pm$ 0.67	19.11 <sup>a</sup> $\pm$ 0.21	13.88 <sup>a</sup> $\pm$ 0.10	3.72 <sup>f</sup> $\pm$ 0.03
F-1	2.02 <sup>d,e</sup> $\pm$ 0.01	49.13 <sup>e</sup> $\pm$ 0.47	16.93 <sup>f</sup> $\pm$ 0.03	12.02 <sup>f,g</sup> $\pm$ 0.08	3.84 <sup>b,c</sup> $\pm$ 0.03
R-2	2.07 <sup>c</sup> $\pm$ 0.02	51.55 <sup>c</sup> $\pm$ 0.53	17.63 <sup>c</sup> $\pm$ 0.17	12.70 <sup>c</sup> $\pm$ 0.08	3.76 <sup>e</sup> $\pm$ 0.03
F-2	2.03 <sup>d</sup> $\pm$ 0.02	49.83 <sup>d</sup> $\pm$ 0.56	17.12 <sup>e</sup> $\pm$ 0.18	12.26 <sup>d</sup> $\pm$ 0.09	3.79 <sup>d,e</sup> $\pm$ 0.03
F-3	2.01 <sup>e</sup> $\pm$ 0.01	48.93 <sup>e</sup> $\pm$ 0.42	16.87 <sup>f</sup> $\pm$ 0.13	11.98 <sup>g</sup> $\pm$ 0.08	3.84 <sup>b,c</sup> $\pm$ 0.03
S-1	2.11 <sup>b</sup> $\pm$ 0.02	52.97 <sup>b</sup> $\pm$ 0.61	18.09 <sup>b</sup> $\pm$ 0.19	12.90 <sup>b</sup> $\pm$ 0.09	3.85 <sup>b</sup> $\pm$ 0.03
FS-1	2.02 <sup>d,e</sup> $\pm$ 0.01	49.23 <sup>e</sup> $\pm$ 0.48	16.95 <sup>f</sup> $\pm$ 0.15	12.09 <sup>f</sup> $\pm$ 0.08	3.82 <sup>c,d</sup> $\pm$ 0.03
FS-2	2.06 <sup>c</sup> $\pm$ 0.01	50.32 <sup>d</sup> $\pm$ 0.46	17.32 <sup>d</sup> $\pm$ 0.15	12.17 <sup>e</sup> $\pm$ 0.06	3.94 <sup>a</sup> $\pm$ 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)

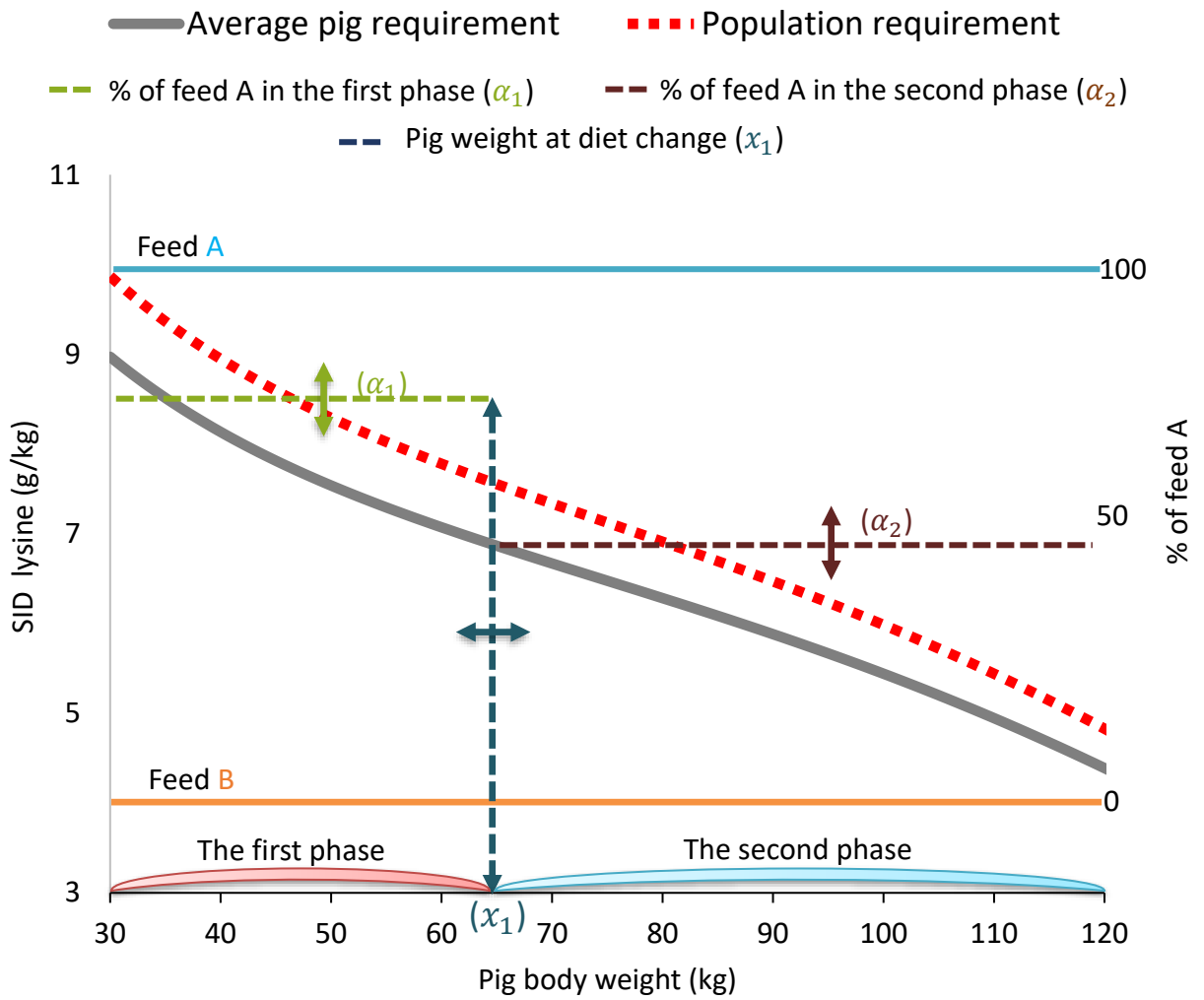


Figure 2

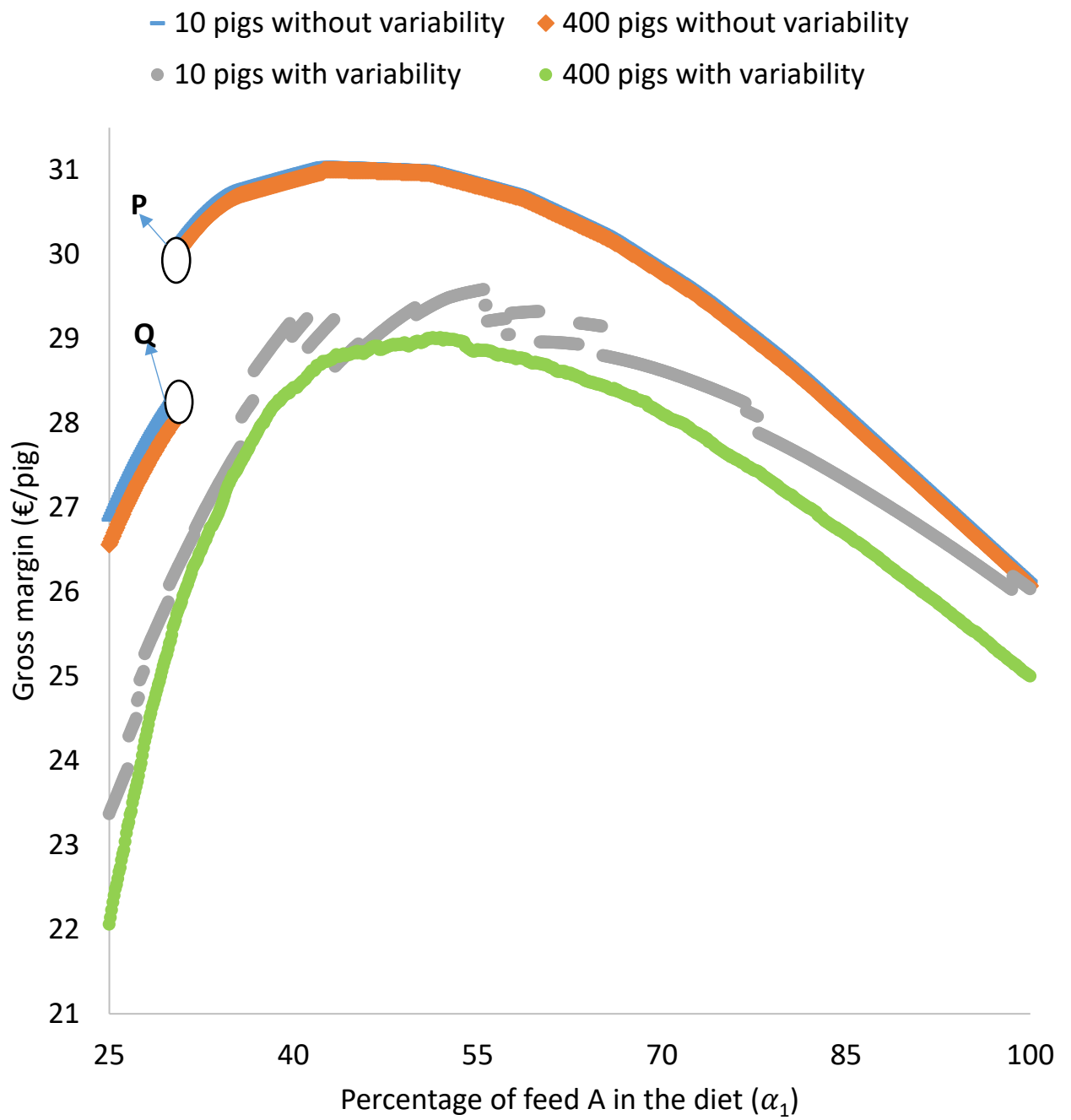


Figure 3

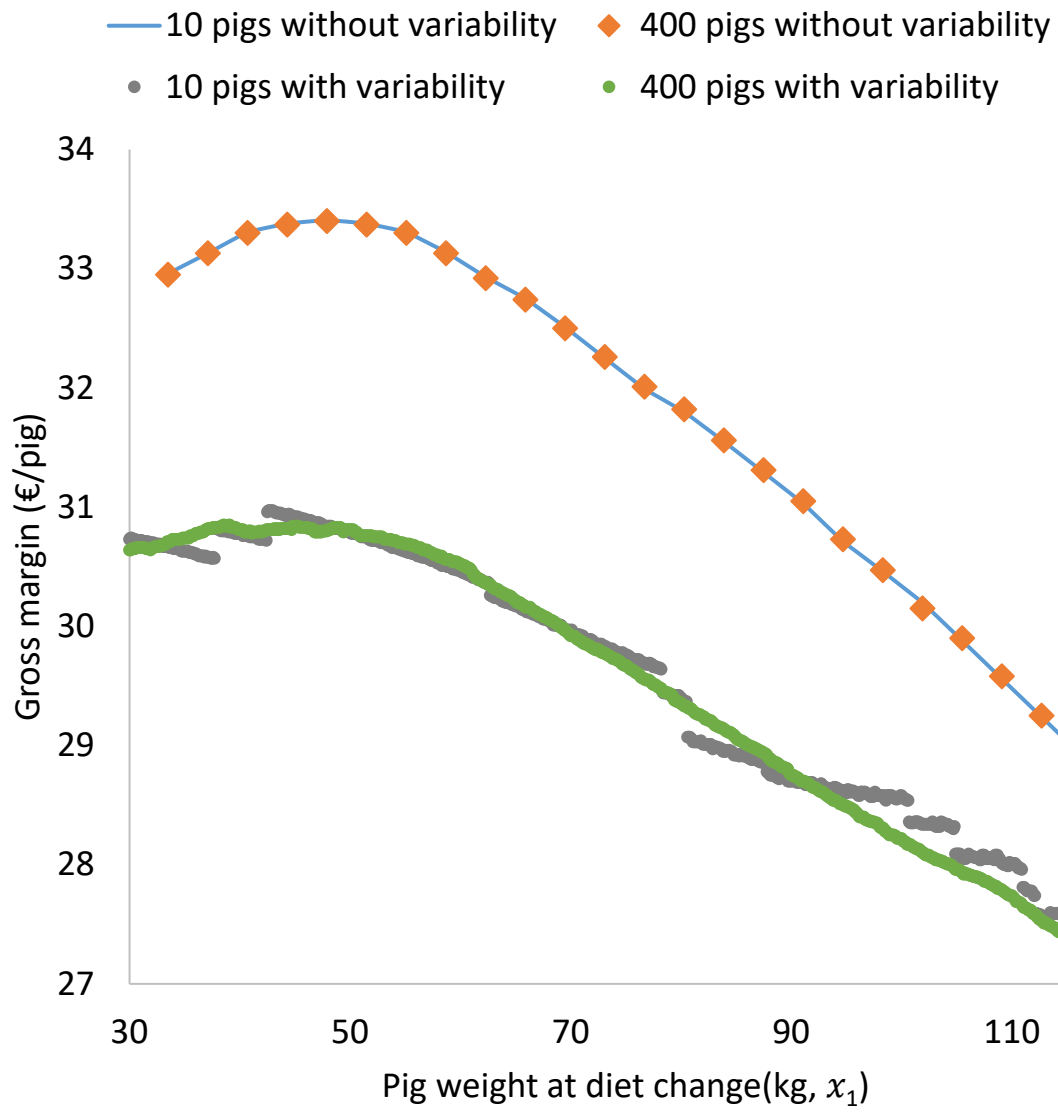


Figure 4

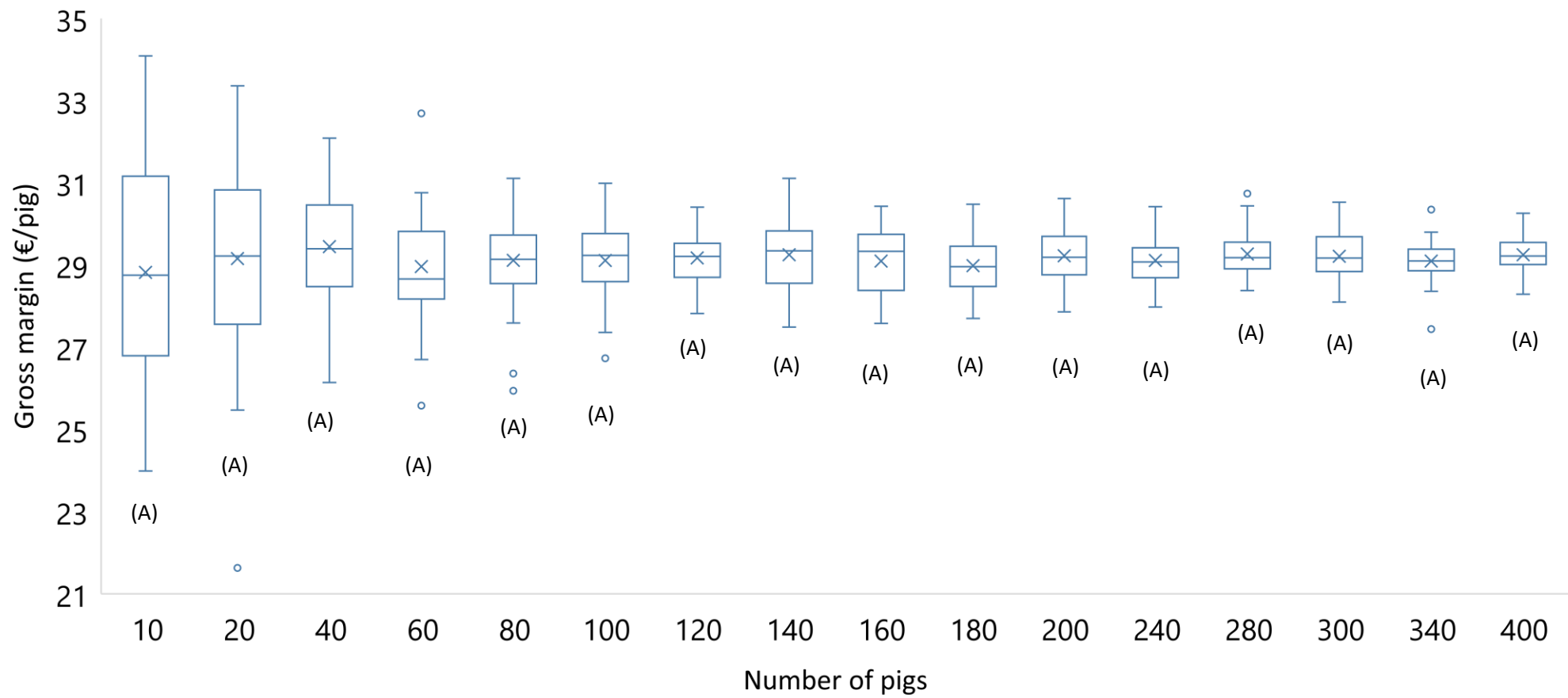


Figure 5



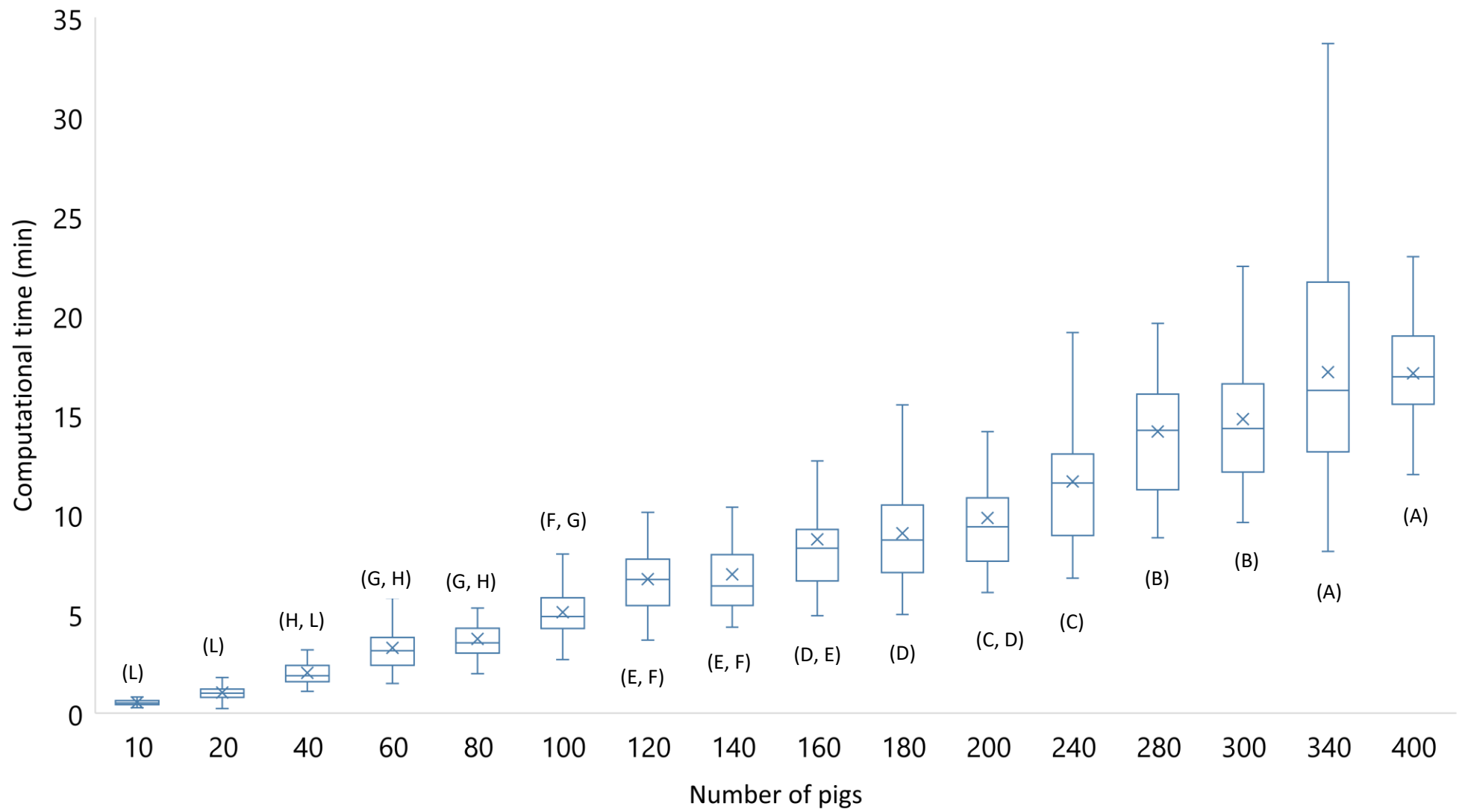


Figure 6

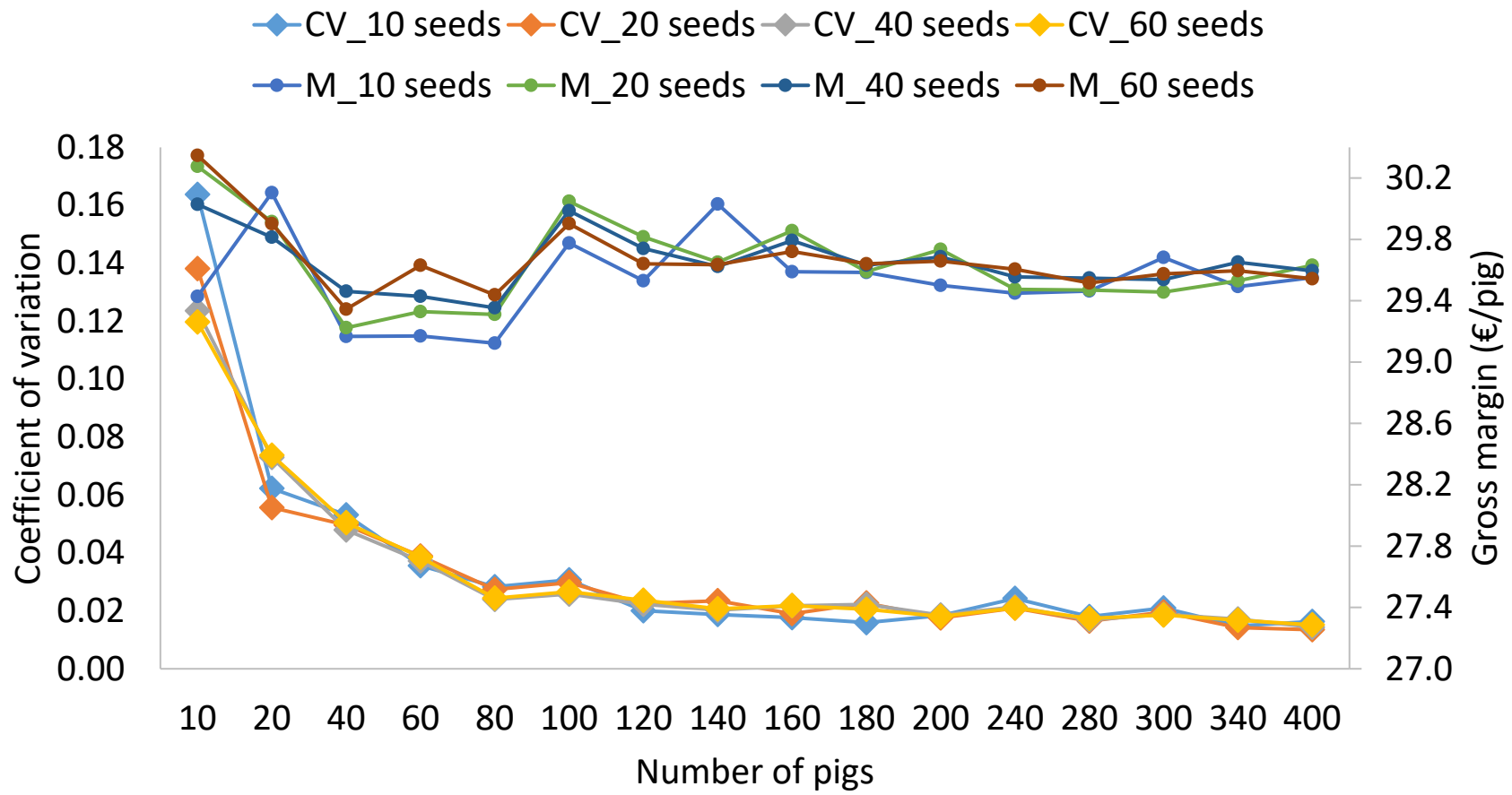


Figure 7

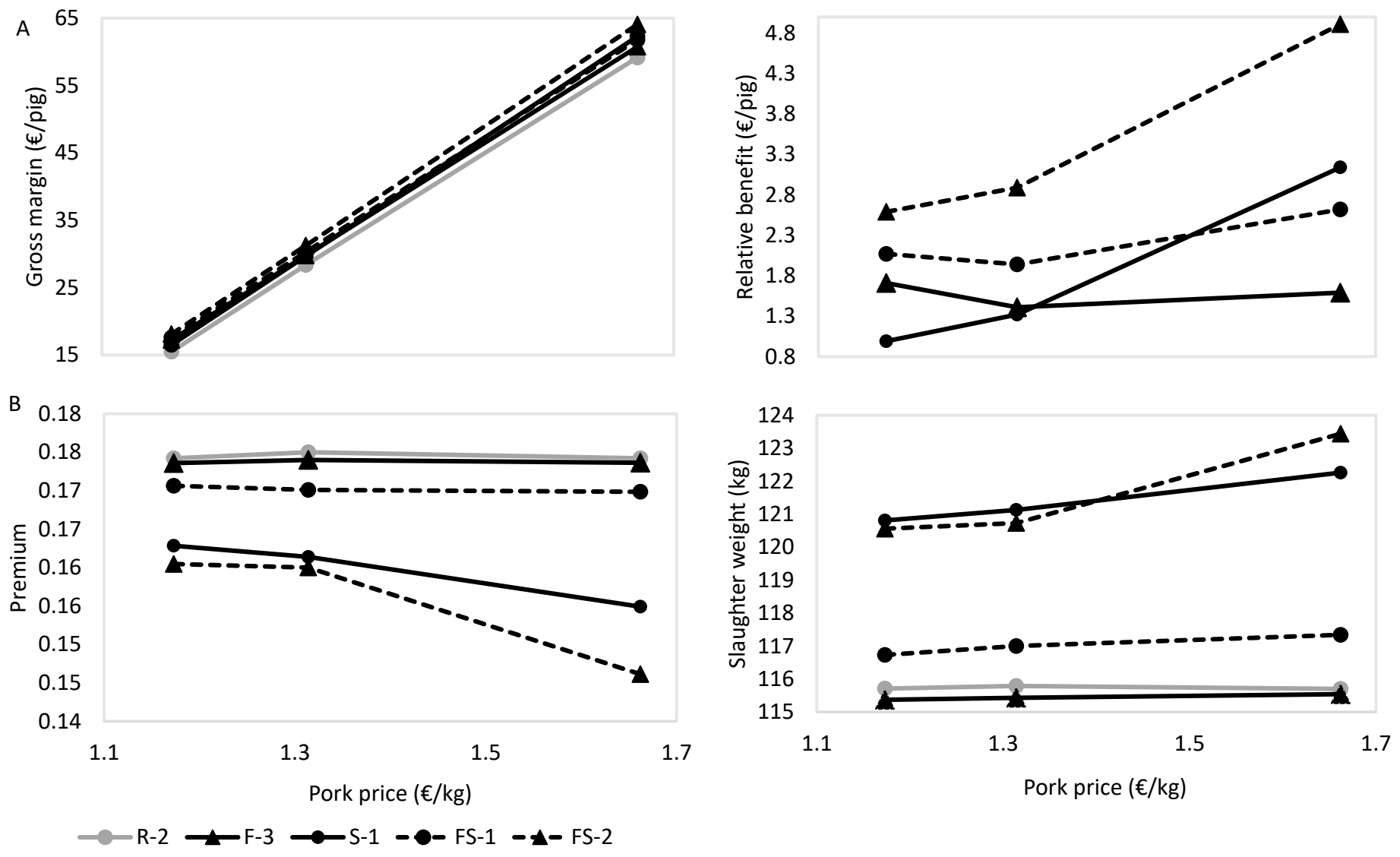


Figure 8

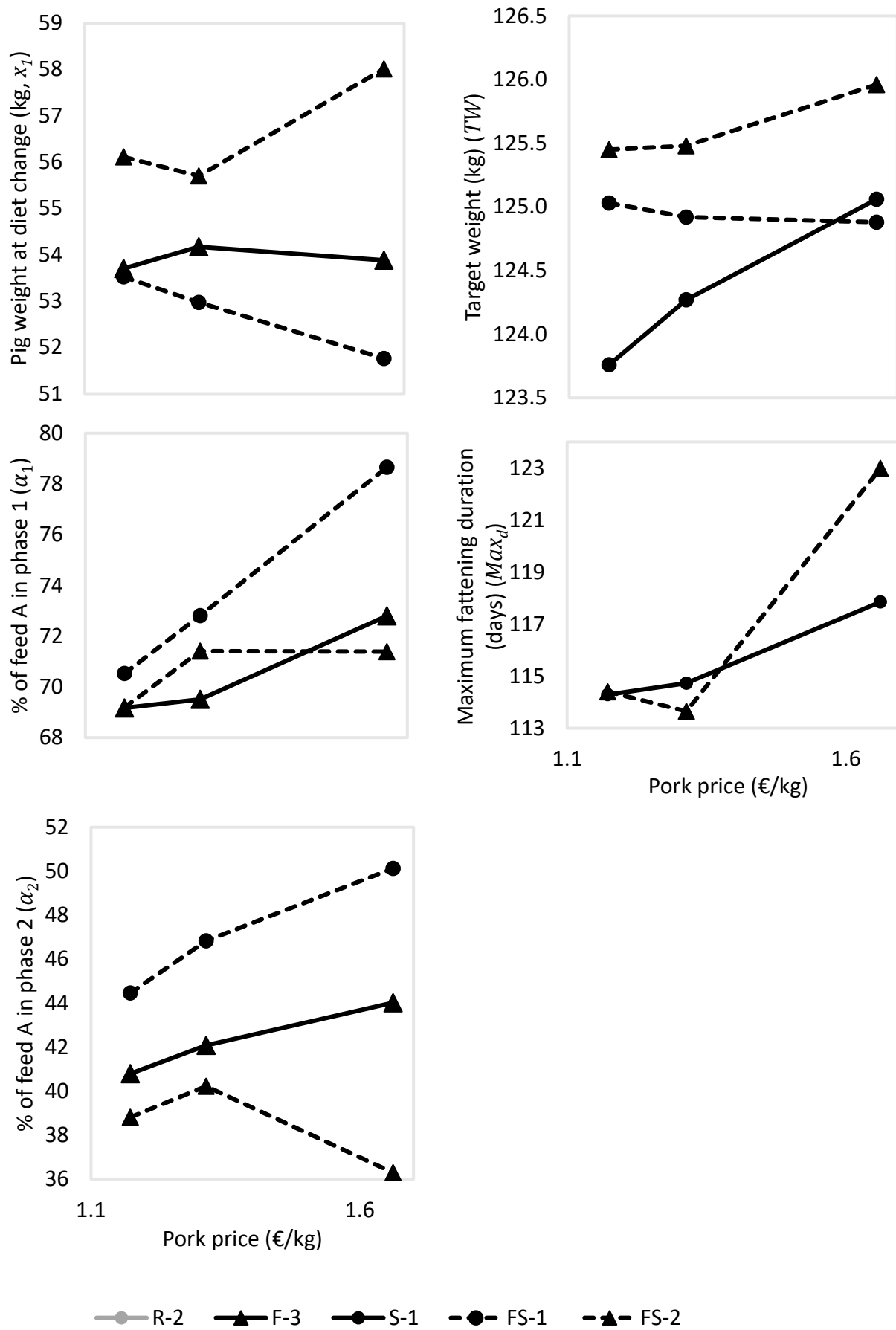


Figure 9

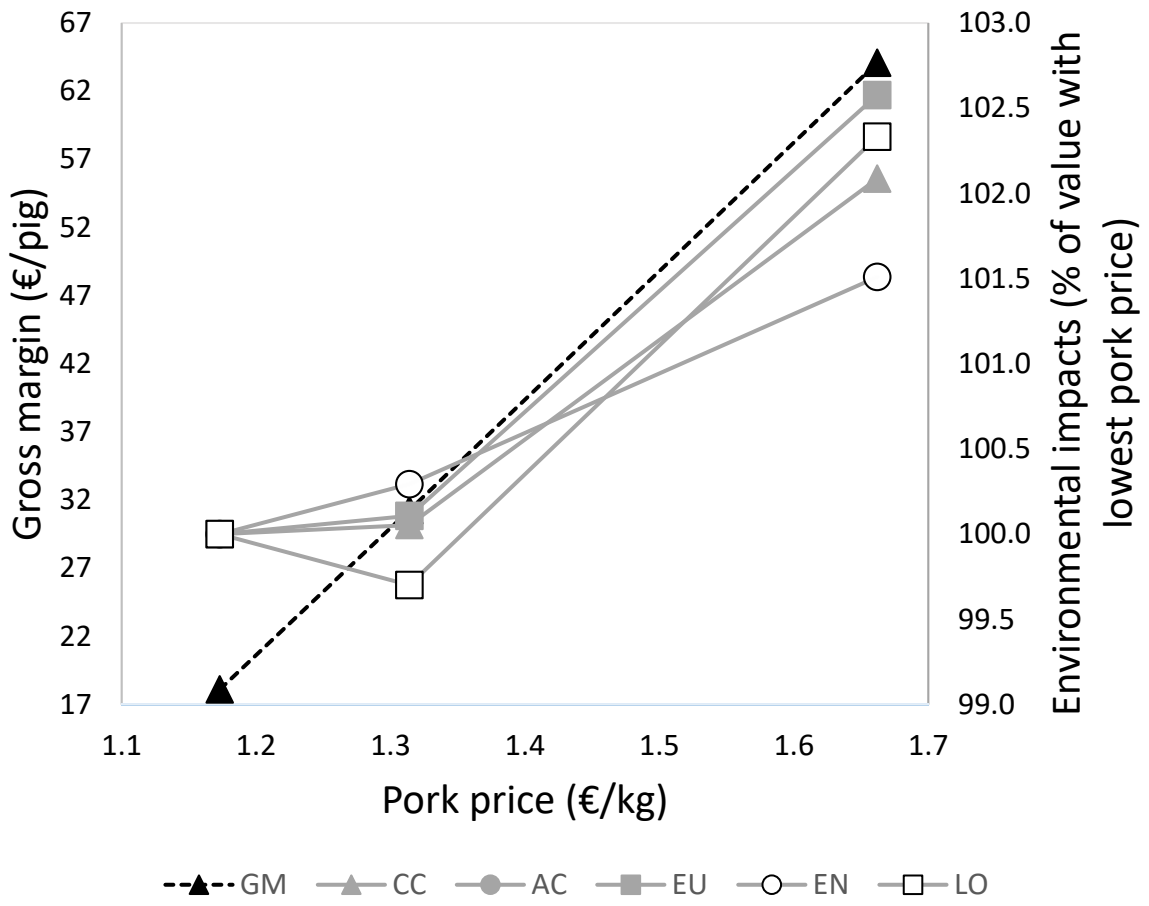


Figure 10