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Guillaume Lenoir, Rafael Munoz Tamayo, Loïc Flatres-Grall, Ingrid David, Nicolas N.C. Friggens

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G. Lenoir[1,2,3*], R. Muñoz-Tamayo[1], L. Flatres-Grall[2], I. David[3] and N. C. Friggens[1]

[1] Université Paris-Saclay, INRAE-AgroParisTech, UMR Modélisation Systémique Appliquée aux Ruminants, 75005 Paris, France; [2] AXIOM, 37310 Azay-sur-Indre, France; [3] GenPhySE, INRAE, ENVT, Université de Toulouse, 31326 Castanet-Tolosan, France; *glenoir@axiom-genetics.com

Abstract

The objectives of this study were to investigate the possibility of characterising animal robustness by using indicators based on the dynamics of energy allocation of the animal and to determine their genetic parameters. A total of 2 140 pigs, from the Piétrain NN Français line, were raised at the AXIOM boar testing station. This farm was equipped with automatic feeding system, recording individual weight and feed intake at each visit. We used a dynamic linear regression model to characterize the evolution of the allocation factor (α_t) between cumulative net energy available, estimated from feed intake, and cumulative weight gain during fattening period. The variance of α_t, that could be interpreted as an indicator of the response of the animal to perturbations/stress, showed moderate heritability (0.27 ±0.08). Our perspective is to further decompose the allocation factor into components to better characterise the robustness phenotype.

Introduction

Livestock farming faces new challenges related to climate change and societal concerns, e.g., animal welfare and use of antibiotics. These challenges require having animals able to adapt to these new conditions, which implies an improvement of robustness while maintaining a high level of production. There is no real consensus on the definition of robustness as well as on the ways to phenotype it. Following the definition of robustness adapted to the context of artificial selection of Knap (2005), we have recently proposed robustness scores estimated from phenotypes commonly available on farm (Lenoir et al., 2021). However, these scores had low heritability indicating the need to find other indicators that can be used for genetic improvement. Development of new technologies in livestock production, such as automatic feeding system, allow recording of longitudinal data over a period (weight, feed intake, feeding duration). Several studies have used such data to quantify robustness and resilience indicators based on deviation between potential of production of an individual and its observed production (Nguyen-Ba et al., 2020; Revilla et al., 2022). Definition and modelling of individual potential are challenging issues in these approaches. The first objective of this study was to investigate the possibility of characterising animal robustness by using indicators based on the dynamics of energy allocation of the animal. Our rationale is that these indicators should reflect the ability of an animal to express or adapt its production potential in the face of changes in the environment relative to other animals that have been raised under the same conditions. To identify these indicators, we followed a modelling approach applied on longitudinal measurements of body weight and feed intake of fattening pigs (35 to 110 kg live weight). The second objective was to estimate the genetic determinism of the resulting indicators and to compare them with other robustness traits.

Materials & Methods

Animals. Pigs from Piétrain NN Français paternal line, free from halothane-sensitivity, of the Axiom company were used in this study. The animals considered in this study were 2 140 entire males raised from January 2019 to April 2021 at the AXIOM boar testing station and born from two different farms. They entered the boar testing station after weaning and were raised in quarantine rooms and in post-weaning rooms for 7 weeks. Then, animals were transferred to fattening rooms when they were 75.3 ±3.4 days of age (34.5 ±6.2 kg BW). They were kept in fattening rooms during 74.8 ±4.0 days until the individual candidate test at around 149.7 ±4.1 days of age (108.8 ±11.5 kg BW). Fattening rooms were equipped with automatic feeding system (AFS) Nedap pig performance testing feeding station (Nedap N.V.; Groenlo, the Netherlands).

Data. During the fattening period, BW (kg) and feed intake (FI - kg) were recorded each time the animal went into the AFS. Other measurements made during the individual test were: average ultrasonic backfat thickness (BF100) and ultrasonic longissimus dorsi thickness (LD100), both adjusted to 100 kg liveweight. Individual average daily gain (ADG) and daily feed intake (DFI) were calculated. The feed conversion ratio (FCR) was calculated as the ratio between the total FI and the weight gain during the fattening period. A phenotype to characterize the robustness (R2) of the candidates was determined from the visual observation performed during the individual test based on Lenoir et al. (2021). The binary trait R2 differentiated animals that were selectable (score 1), from those that were dead or not selectable (score 0). The ABC index developed by Revilla et al. (2021) was calculated using weight measured by AFS for each animal alive at the end of the fattening period. The trait ABC was the accumulated difference (area) between a theoretical unperturbed growth curve and the perturbed curve.
After pre-treatment process of data recorded by AFS, the weight (W_t - kg) and the feed intake (F_t - kg) for each fattening day were estimated, where t was time in days since the transfer to fattening room. Then, F_t was converted in net energy intake (EI_t) by using a factor of 9.85 MJ/kg of NE. The net energy available at day t (NEA_t) was the difference between EI_t and the net energy maintenance requirements at day t (MR_t). The value of MR_t was estimated according to Noblet et al. (2016), $MR_t = 1.05 * W_t^{0.6} * 0.74$.

Modelling growth allocation. We could represent the link between cumulative NEA (CNEA) and cumulative weight gain (CW) by a standard linear regression for each animal (1).

$$CW_t = \alpha\, CNEA_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim N(0,\sigma^2) \tag{1}$$

Where CW_t is the time series of cumulative weight gain (kg) at day t; $CNEA_{t-1}$ is the cumulative net energy available (MJ) at day $t-1$; α is an allocation factor of energy to weight gain. We assumed in this study that a perturbation is linked with a change in the allocation of energy available to the growth. Therefore, the relationship between CW and CNEA evolves over time. To characterize this evolution, we used a dynamic linear regression model (Petris et al., 2009) built with two equations: an observation equation (2), relating cumulated weight gains and cumulated NEA, and a system equation (3), describing the changes in α_t (unobserved state variable) from day to day according to a stochastic process.

$$CW_t = \alpha_t CNEA_{t-1} + v_t, \qquad v_t \sim N(0,\sigma_v^2) \tag{2}$$

$$\alpha_t = \alpha_{t-1} + w_t, \qquad w_t \sim N(0,\sigma_w^2) \tag{3}$$

The model has been built using the function dlmModReg of the package dlm of R (Petris et al., 2009). It included two unknown parameters (σ_v^2 and σ_w^2) that were estimated by maximum likelihood with the function dlmMLE. The values of α_t were calculated independently for each animal with a Kalman smoother algorithm (function dlmSmooth). For each individual, using the estimated α_t across time, we further calculated two traits: the mean (MA) and the variance (VA).

Genetic parameters estimation. Genetic parameters were estimated using ASReml 3.0 software (Gilmour et al., 2009) using the restricted maximum likelihood method (REML). The fixed effect was the fattening group (33 levels). In addition, two random effects were included in the model: common litter effect and genetic additive effect of the animal. Traits ABC, MA and VA were standardized on a mean of 0 and a standard deviation of 1. Firstly, variance and covariance components were estimated with a 4-trait linear animal model including traits under selection (ADG, FCR, BF100 and LD100). Secondly, to estimate heritability for each non-selected trait (MA, VA, DFI, ABC and R2) and their genetic correlations with the traits under selection, 5-trait linear animal models including the 4 traits under selection and 1 trait to be estimated were used. R2 was considered as a continuous phenotype. Thirdly, to estimate genetic correlations between MA and VA with the other non-selected traits, 2-trait linear animal models were performed. The pedigree contained 3 944 animals across 24 generations.

Results

Table 1. Descriptive statistics (Mean and *SD*: standard deviation), heritability (h^2 ± standard error) for studied traits and genetic correlations (r^2a ± standard error) of mean of α_t (MA) and variance of α_t (VA) with studied traits.

	ADG *kg/d*	BF100 *mm*	LD100 *mm*	FCR *kg/kg*	DFI *kg/d*	R2 *no unit*	ABC *no unit*	MA *kg/MJ*	VA *kg²/MJ²*
Mean	0.992	6.6	68.0	2.26	2.240	0.80	30,726	0.094	0.0005
SD	*0.108*	*0.8*	*5.3*	*0.19*	*0.287*	/	*24,764*	*0.019*	*0.0046*
h^2	0.36[1] ±0.05	0.32[1] ±0.07	0.41[1] ±0.07	0.15[1] ±0.05	0.31[2] ±0.07	0.08[2] ±0.04	0.06[2] ±0.03	0.16[2] ±0.05	0.27[2] ±0.08
r^2a MA	-0.64[2] ±0.14	-0.52[2] ±0.16	-0.59[2] ±0.17	-0.79[2] ±0.13	0.28[3] ±0.10	-0.17[3] ±0.26	0.57[3] ±0.32	/	-0.15[3] ±0.26
r^2a VA	-0.04[2] ±0.19	0.09[2] ±0.41	-0.02[2] ±0.18	-0.41[2] ±0.21	-0.36[3] ±0.16	-0.20[3] ±0.27	0.52[3] ±0.29	-0.15[3] ±0.26	/

ADG = average daily gain; BF100= backfat thickness estimated at 100kg; LD100= longissimus dorsi thickness estimated at 100 kg; DFI= average daily feed intake; R2 = robustness trait; ABC= resilience index

[1]Estimates from a 4-traits multiple trait model (ADG, FCR, BF100, LD100)

[2]Estimates from a 5-traits multiple trait model (ADG, FCR, BF100, LD100 and the trait under consideration)

[3]Estimates from a bivariate model (2 traits under consideration)

For traits ABC, MA and VA, descriptive values are presented in Table 1 (raw values before standardization). For the traits under selection (ADG, FCR, BF100 and LD100) and DFI, heritability estimates were moderate, from 0.31 ±0.07 to 0.41 ±0.07, expect for FCR with a lower value (0.15 ±0.05). Precisions of estimates were quite low, given the sample size. Heritability of MA (0.16 ±0.05) was similar to those estimated for FCR. For the 3 robustness traits, heritabilities were low for ABC and R2, 0.06 ±0.03 and 0.08 ±0.04 respectively, and moderate for VA (0.27 ±0.08). The trait MA had moderate to high negative genetic correlations with production traits (-0.52 to -0.79). It was positively correlated with DFI (0.28). Genetic correlations between VA and ADG, BF100 and LD100 were not significantly different from 0. The trait VA was moderately correlated with ABC (0.52 ±0.29) and negatively with FCR and DFI. The three genetic correlations between the traits MA, VA and R2 (ranging from -0.15 to -0.20) were not significantly different from 0. Several estimates of genetic correlations had large standard errors and should be interpreted with caution.

Discussion

The traits MA and FCR were quite similar, with close heritability estimates and a strong and favourable correlation. This correlation looks different from 1, which could imply that the trait MA captures other elements of energy allocation than FCR. The strong and unfavourable genetic correlation with ADG could be related on the way these two traits were estimated. They were measured over an identical period for all individuals but were not standardized between starting and finishing weights (ADG 30-110kg). Some of the animals tested reached their maturity weight before the end of testing period, which leaded to a drop in feed efficiency. The trait MA described the average allocation of net energy in growth during fattening period. This trait seems to be an interesting way to phenotype feed efficiency but the relationship between evolution of α_t over time and degree of maturity, regardless maintenance requirements, needs further investigation. The trait MA was also unfavourably correlated to the resilience indicator ABC, suggesting that an increase of energy allocation increases the risk of deviation of potential ADG in case of an environmental perturbation. In contrast, VA was favourably correlated with robustness trait and moderately with ABC trait. The trait VA, variation of α_t over testing period, could be interpreted as an indicator of the response of the animal to perturbations/stress. Indeed, more robust animals are less impacted by perturbations, we assumed that these animals would have a "more stable" α_t and consequently a lower value of VA. Heritability of this trait was higher than the other robustness traits. This makes it possible to consider a selection on the trait VA. A selection to reduce the variance of α_t would have a negative impact on FCR genetic potential, due to the moderate negative correlation with FCR, and no (or slightly positive) effect on the mean of α_t.

These preliminary results show the value of using the dynamic linear regression method in order to estimate time-trends in allocation (α_t) and to define robustness indicators on the basis of energy allocation. Our perspective is to further decompose the allocation factor into components such as degree of maturity, sensitivity to perturbations, etc in order to better characterise the robustness phenotype and propose useful indicators of robustness for genetic selection.

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