A NEW ALGORITHMIC APPROACH TO BETTER PREDICT EATING QUALITY FROM REARING PRACTICES

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I. INTRODUCTION

Meat is a highly nutritious food source that plays a significant role in the global economy. The meat industry has experienced considerable growth in the past few decades, driven by increasing demand for animal protein from growing populations worldwide [1]. However, consumers are now becoming more aware of the impacts of meat production on animal welfare and the environment. As a result, consumer behavior has shifted towards healthier, more sustainable, and animal welfare food, leading to a decline in meat consumption and a demand for high-quality meat (in terms of sensory as well as nutritional quality). To address these challenges, the meat industry needs to adopt new strategies that optimize meat quality and meet consumer demands [2-3]. One of these approaches is to use husbandry practices to estimate meat quality at an early stage, in order to reach an optimal quality and to answer the demand of the consumers. A methodological approach and the corresponding algorithm are presented to meet these objectives using a chicken dataset.

II. MATERIALS AND METHODS

The methodology is inspired by the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [4], to optimize husbandry practices for various animal breeds and enhance meat quality. Firstly, we establish the decision space, which consists of variables related to rearing management, while the objective space contains the variables associated with the meat quality we aim to optimize. Briefly, this algorithm iteratively generates new populations by employing genetic operators such as crossover and mutation to produce offspring and explore novel possibilities within the global solution space. The new population is evaluated, and the optimal set of solutions is selected. This process is repeated for a predetermined number of generations until the best possible solution is reached (Fig.1). To guarantee the accurate and precise prediction of each objective's fitness value, a multiple linear regression model is utilized, followed by an Akaike Information Criterion approach to select the most pertinent model for each objective [5]. Once a new population is generated and the fitness score is estimated, a selection of the best individuals is done using the Pareto front method, which identifies the non-dominant solutions within the multi-objective space representing the best possible solutions. This strategy yields optimal breeding practices for each animal breed/type, taking into account both meat quality variables and breeding management factors. To prevent the algorithm from getting trapped in a local optimum, a crowding distance technique is utilized to maintain population diversity. This technique enables the exploration of the entire search space and identification of the global maximum.

III. RESULTS AND DICUSSION

The study analyzed a set of data for 7,843 fillets collected from commercial slaughterhouses as part of a survey conducted by ITAVI and INRAE, focusing on the four main French production systems (Label Rouge, Certified, Standard and Heavy Broilers). The data differed based on animal type, age, weight at slaughter, and rearing practices. The simulation was designed to optimize the quality of breast meat by setting the lowest lipid content while minimizing cooking loss and meat toughness. This was achieved by utilizing rearing factors such as body weight, age, and carcass holding period. The results demonstrate that the optimization of solutions tends to converge quickly towards the predefined objectives (Fig.2). Age, body weight and carcass holding period variables were found to be significant independent explanatory factors of dependent variables related to quality for Standard, Certified, and Label categories. However, for the Heavy Broiler category, variables related to body weight and carcass holding period contribute more significantly to meat quality evaluation. For this reason, the model only retained these two variables to estimate meat quality. Considering the various rearing practices, it is observed that the lipid content is lower in Label breeding compared to Certified, Standard, and Heavy Broiler breeding. Regarding cooking loss, Heavy presents the highest loss, followed by Label, then Certified, and finally Standard broilers, which has the lowest loss. In terms of meat toughness, Standard is the most tender, followed by Heavy, Certified, and finally Label Broilers.

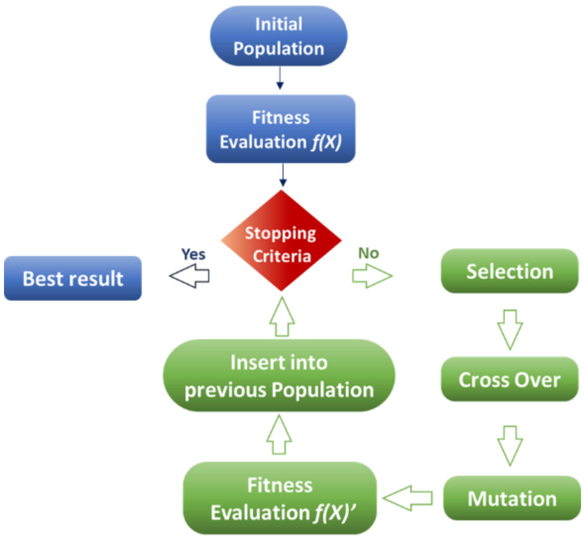

Figure 1. Conceptual view of the genetic algorithm, an evolutionary-inspired optimization method for generating optimal or near-optimal solutions.

Breeding practices | Objective

	Standard	Certified	Label	Heavy
Generation	11	6	8	8
BW (kg)	2.39	1.80	2.42	4.78
Age (day)	35	44	92	N/A
Carcass Holding Period (hour)	30	48	8	3
Lipids (%)	1.62	1.19	0.95	1.70
Toughness (N)	9.50	17.15	20.02	15.04
Cooking loss (%)	10.65	12.36	12.44	12.77

Figure 2. Representation the algorithm-driven simulation convergence, identifying the most favorable solution based on the selected objective (red) through the assessment of meat quality using the selected breeding practices (green).

IV. CONCLUSION

This methodological approach allows to evaluate meat quality, centered around rearing practices. By analyzing a chicken dataset, the proposed algorithm demonstrates a novel strategy for optimizing diverse rearing methods adapted to the type of breeding. However, rapid convergence after a limited number of iterations suggests the possibility to quickly reach an optimum. To enhance this methodology, it is crucial to investigate advanced approaches, verify the optimization process, and establish whether we have achieved a local or global maximum. This comprehensive evaluation will ultimately lead to a more robust and precise assessment of meat quality.

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