Estimation the Effects of Shape Traits on Egg Shell Breaking Strength using MARS

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***Abstract*—** This study aimed to estimate the egg shell breaking strength (ESBS) with the external egg quality traits such as egg weight (EW), specific gravity (SG), shape index (SI) egg width (EWi) and egg height (EH) using Multivariate Adaptive Regression Splines. For this aim 719 white shell color eggs were used as a data set. There was no high relation obtained with the egg shell breaking strength (ESBS) when the highest positive correlation obtained between EW and EWi and a negative highest relation was observed between EH and SI. The results of this study showed that the egg shell breaking strength cannot be reliably estimated by the external egg quality traits such as egg weight (EW), specific gravity (SG), shape index (SI) egg width (EWi) and egg height (EH) using Multivariate Adaptive Regression Splines.

***Keywords*—** Egg Shell Breaking Strength, Chicken Egg, External Egg Quality Traits, MARS, Modelling and Estimation

I. Introduction

An increase of great production has been supplied in laying hens with the effects of genetic improvement, quality of feed and breeding techniques in the last five decades. In the future this increase will not be in the same level, but the studies about egg yolk, albumen and shell quality will continue to increase [1][2]. Improving the shell quality will be another important subject to reduce the economic losses via cracks and the breakings of the egg [2]. It is known that increased egg size reduced the egg shell thickness and egg shell breaking strength [3]. Estimation of egg shell breaking strength and the determination of the effective external egg quality traits on the egg shell breaking strength is essential for the industry.

The Multivariate Adaptive Regression Splines (MARS) algorithm was proposed by Friedman [4] for making predictions based on quantitative features. To solve regression-type problems, the MARS algorithm uses a non-parametric regression procedure that allows better recognition of linear, nonlinear and interaction effects between response and explanatory variables. The MARS algorithm was developed from the CART algorithm. In solving regression-type problems, there is no need for any assumptions about both the distribution of variables and the relationships between response and explanatory variables in this algorithm [5]. The algorithm has various slopes in the training data set, splitting up the individual segmented linear segments (splines) [5][6]. The splines relate without problems and form connection points called "knots". Candidate nodes are randomly placed within the range of each estimator, so the model estimation made with the MARS algorithm is more flexible and interpretable with the help of piecewise linear regressions [6].

This study aimed to estimate the egg shell breaking strength (ESBS) with the external egg quality traits such as egg weight (EW), specific gravity (SG), shape index (SI) egg width (EWi) and egg height (EH) using Multivariate Adaptive Regression Splines.

II. Materials And Methods

As the data material total 719 white shell color eggs were used, which was taken from another study.

The model used by the algorithm to estimate egg shell breaking strength from explanatory variables that affect egg shell breaking strength, such as egg weight, was given below:

$$\hat{y} = \beta_0 + \sum_{m=1}^{M} \beta_m \prod_{k=1}^{K_m} h_{km}\left(X_{v(k,m)}\right)$$

where $\hat{y}$ is the predicted value for ESBS, β_0 is an intercept, β_m is the basic function coefficient, K_m is the parameter that limits the interaction order, the h_{km} ($X_{v(k,m)}$) term is called the basis function, and v(k,m) is an index of the explanatory variable in the m^{th} component of the k^{th} product. The basic functions that reduce the performance of the model obtained after the forward and backward pass stages are eliminated due to the generalized cross-validation error (GCV) [7].

RMSE, SDR, CV, PI, RAE, MAPE, MAD, R^2 and AIC goodness-of-fit criteria were used to evaluate the performance of the model. The model performances were evaluated according to the lowest RMSE, SDR, PI, RAE, MAPE, MAD and AIC values and the highest R^2 value [6].

Statistical evaluations were carried out using the R software. To provide information about the structure of the data, descriptive statistics were performed. Descriptive statistics for all variables were estimated using "*psych*" package in the R environment. The "*caret*" packages in the R software were used to analyze the MARS algorithm. To evaluate the MARS model performances, the "*ehaGoF*" package was employed [6].

III. Results And Discussion

The Pearson correlation coefficients among the variables was given in Fig 1.

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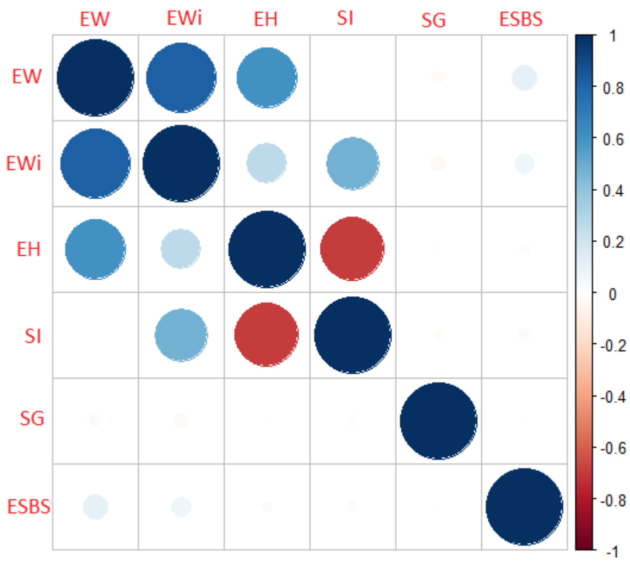

Fig. 1. Pearson correlation coefficients.

There was no high relation obtained with the egg shell breaking strength (ESBS) when the highest positive correlation obtained between EW and EWi and a negative highest relation was observed between EH and SI.

The Multivariate Adaptive Regression Splines algorithm’ characteristic insignificant explanatory variables of egg width (EWi) egg height (EH), and shape index (SI) were removed from the model on the estimation of egg shell breaking strength. The obtained model was given in Table I and the Goodness-of-fit criteria results for the model was given in Table II.

TABLE I: MODEL PARAMETER ESTIMATES

	Coefficients 1
Intercept	3.896355
h(56.7-EW)	-0.079671
h(1.095-SG)	-83.158044
h(56.7-EW)*h(1.075-SG)	13.516175
h(EW-56.7)*h(1.07-SG)	7.840012

According to the obtained model there was an interaction between egg weight and specific gravity on the estimation of egg shell breaking strength. The differences of SG from the value of 1.095 had a high negative effect on the egg shell breaking strength. Interaction terms had positive effect on the egg shell breaking strength (Table I).

When the Adjusted coefficient of determination (ARsq) values were examined it can be seen that the model fit wasn’t high enough to decide to make estimation for both in train and test sets. AIC and CAIC values showed that the train set results were more reliable than the test set results as expected (Table II).

TABLE II: GOODNESS-OF-FIT CRITERIA RESULTS FOR THE MARS MODEL

Criteria	Train	Test
Root mean square error (RMSE)	0.777	0.761
Relative root mean square error (RRMSE)	27.025	26.470
Standard deviation ratio (SDR)	0.781	0.802
Coefficient of variation (CV)	27.050	26.530
Pearson's correlation coefficients (PC)	0.624	0.598
Performance index (PI)	16.639	16.565
Mean error (ME)	0.000	0.016
Relative approximation error (RAE)	0.065	0.063
Mean relative approximation error (MRAE)	0.011	0.017
Mean absolute percentage error (MAPE)	28.933	26.374
Mean absolute deviation (MAD)	0.623	0.623
Coefficient of determination (Rsq)	0.390	0.357
Adjusted coefficient of determination (ARsq)	0.384	0.342
Akaike's information Criterion (AIC)	-243.791	-106.722
Corrected Akaike's information criterion (CAIC)	-243.670	-106.433

IV. CONCLUSION

The results of this study showed that the egg shell breaking strength cannot be reliably estimated by the external egg quality traits such as egg weight (EW), specific gravity (SG), shape index (SI) egg width (EWi) and egg height (EH) using Multivariate Adaptive Regression Splines. To achieve this objection more variables should be examined with greater number of samples.

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