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Original Research Article

NON-LINEAR MODELING AND ALGORITHM DEVELOPMENT FOR POULTRY HENS

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Abstract: In present study, modeling poultry egg production has been carried out. Seven nonlinear models are evaluated for fitting the average weekly flock poultry egg production. Among the models considered, compartmental model due to McMillan *et al.*, 1970, which is a combination of monomolecular and an exponential function is found to be superior. When ANN models are developed for the same data, it is found that ANN model using RBF architecture is found to be better compared to the ANN model based on MLP architecture and further ANN using RBF architecture is better than the best nonlinear model identified for this data.

Keywords: Egg Production, Compartmental Model, Non-linear regression Models.

Introduction*:* Egg production in poultry is a complex quantitative trait and shows considerable individual variation over the laying period. Number of eggs produced per unit of time is the basis for assessing egg production efficiency. Egg production curve describes the relation between number of eggs and time of laying period. The use of mathematical models to estimate egg production curves is of great importance for evaluating egg production over the laying cycle. These models may be used to estimate the financial loss caused by a decline in egg production, as evinced by a deviation from the expected curve[1-5].

As hens do not produce eggs on a daily basis and pauses are inevitable, daily egg production is usually summarized on a weekly basis to measure their capacity for egg production. Poultry egg production when summarized on a weekly basis, rapidly increases to a peak, persists for some time and gradually decreases. A typical weekly egg production curve for a flock increases during the first 8 or 9 weeks of production and then decreases at end of the production period. Poultry egg production is usually modeled using different nonlinear regression models wherein the model parameters can be interpreted in terms of the biological characteristics of the animal[6-8].

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One of the most important uses of an egg production model is to predict total egg production based on partial records[9]. Prediction plays an important role in early selection, production planning and economic decision making[10-11].

In this study, several nonlinear regression models have been evaluated for its suitability in describing the average weekly egg production of a flock of white leghorns reared in a hot and humid coastal area Sehore in Madhya Pradesh, India.

Materials and Methods: Data on daily egg production data of 481 White Leghorns (WL) over a 53-week period of egg laying from 19th week to 71st week of age (380 days) collected from the poultry farm of RIVER, Sehore, India has been summarized on a weekly basis and utilized for this study.

From the egg production data, the Hen Day Egg Production (HDEP) of a flock is calculated as $\frac{(\text{Number of egg produced})}{(\text{Number of hens alive})} \times 100$ on a weekly basis and used for analysis.

The mathematical forms of the models considered are given as follows:

M1: Incomplete Gamma model (Wood, 1967):

$$y_t = a\, t^b\, e^{(-ct)} + \varepsilon_t$$

Where y_t is the egg production during time t

a, b, c are the parameters, ε_t is the error associated with y_t.

M2: Modified Incomplete Gamma model (McNally, 1971)

$$y_t = a\, t^b\, e^{(-ct+d\sqrt{t})} + \varepsilon_t$$

Where y_t is the egg production during time t

a, b, c, d are the parameters, ε_t is the error associated with y_t.

M3: Logistic model (Nelder, 1961)

$$y_t = a\{1-e^{b-ct}\}^{-1}\, e^{-dt} + \varepsilon_t$$

Where y_t is the egg production during time t

a is the asymptotic value of production at peak,

b is the value associated with the growth of the curve, c is a constant,

d is the value associated with the persistency of egg production

εt is the error associated with y_t.

M4: Compartmental model (McMillan et al., 1970)

$$y_t = a\{1-e^{-b(t-c)}\}\, e^{-dt} + \varepsilon_t$$

Where y_t is the egg production during time t

a is the potential maximum egg production

b is the rate of increase in egg laying

c is the initial period of egg laying

d is the rate of decrease in egg laying

ε_t is the error associated with y_t.

M5: Double Compartmental model (McMillan, 1981)

$$y_t = a\{e^{-bt}-e^{-ct}\} + \varepsilon_t$$

Where y_t is the egg production during time t

a, b and c are constants, ε_t is the error associated with y_t.

M6: Modified Compartmental model (Yang et al., 1989)

$$y_t = a\{1-e^{-b(t-c)}\}^{-1}\, e^{-dt} + \varepsilon_t$$

Where y_t is the egg production during time t

a is scale parameter,

b is the reciprocal indicator of variation in sexual maturity

c is the mean age of sexual maturity,

d is the rate of decrease in laying ability, ε_t is the error associated with y_t.

M7: Logistic Curvilinear model (Cason and Britton, 1988)

$$y_t = a\{1-be^{-ct)}\}^{-1}\, e^{-dt} + \varepsilon_t$$

Where y_t is the egg production during time t

a, b, c, d are the parameters, ε_t is the error associated with y_t.

Results and Discussion: All the models mentioned above are fitted to the weekly hen day egg production. The estimated model parameters along with the standard error together with the goodness of fit statistics namely R2, MAE, MSE, AIC and Chi-square values for different models are given in Table 1. The graph depicting the observed and predicted weekly HDEP for the various models (M1 to M7) is shown in figure 1-2. The Chi-square values (Table 1) of all the models are found to be non-significant indicating that all the models fitted the data well. The best-fitted model is decided based on the values of R2, MAE, MSE and AIC. It is observed that for weekly HDEP, model M2 namely, Compartmental model due to McMillan et al., 1970 had the highest R2 value of 92.4% and the lowest MAE, MSE and AIC values of 2.41, 10.85 and 134.4 respectively than the corresponding values of the other models. However, the values of goodness of fit statistics of logistic model (M3), modified compartmental model (M6) and the Logistic Curvilinear model (M7) are very close to the corresponding values of Compartmental model (M4).

Table 1: Parameter estimates of NL regression models and measures of goodness of fit values for weekly HDEP (n=53).

Model	**Parameters**				**Goodness of fit criterion**				**Chi-Square**
	a	b	c	d	R^2	MAE	MIC	AIC	
M_1	47.144 (4.175)	0.307 (0.047)	-0.016 (0.002)	-	56.5%	5.05	61.33	224.2	53.33^{ns}
M_2	109.721 (12.429)	1.57 (0.187)	-.075 (0.012)	-1.445 (.198)	82.1%	3.34	25.77	180.2	26.116^{ns}
M_3	86.854 (1.158)	4.212 (0.646)	2.254 (0.334)	0.003 (0.000)	91.2%	2.53	12.64	142.5	8.401^{ns}
M_4	88.332 (1.185)	0.835 (0.078)	0.889 (0.053)	0.003 (0.000)	**92.4%**	**2.41**	**10.85**	**134.4**	6.66^{ns}
M_5	90.823 (2.102)	0.004 (0.001)	0.435 (0.040)	-	82.3%	3.01	24.99	176.59	27.04^{ns}
M_6	86.854 (1.158)	2.258 (0.334)	1.866 (0.068)	0.003 (0.000)	91.2%	2.53	12.64	142.5	8.401^{ns}
M_7	86.854 (1.158)	67.520 (43.665)	2.258 (0.334)	0.003 (0.000)	91.2%	2.53	12.64	142.5	8.403^{ns}

The figure in parentheses represents the standard error of respective parameters. ns- not significant.

Conclusion: Among the nonlinear regression models considered for fitting, compartmental model due to McMillan et al., 1970 performs best for describing weekly hen day egg production based on superior goodness of fit criterion, validation using an independent data set and also based on the predictive ability using part records. When the same data is used for fitting ANN models using MLP and RBF architectures, ANN model using RBF architecture performs better. Further, it is found that ANN model using RBF architecture is found to be better than the best nonlinear regression model namely, compartmental model due to McMillan et al., 1970. Thus, artificial neural network modelling has been found to be a useful alternative to nonlinear regression. However, even though ANN has given slightly improved fit compared to nonlinear regression for this data, some more ANN architectures can be explored for further improving the fit.

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