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Forecasting egg production curve with neural networks

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PALABRAS CLAVE ADICIONALES

Modelado de curvas.
Modelo matemático.
Avicultura.
Polinomios segmentados.

RESUMEN

La comparación entre la curva de producción real del huevo y la gráfica propuesta por las pautas de gestión, tiene como objetivo la evaluación continua del rendimiento. Los objetivos de este estudio fueron comparar la capacidad de la curva de ajuste de la producción diaria de huevo de Lokjorst (LM), la red neuronal del perceptrón multicapa (MP) y las redes neuronales recurrantes de Jordania y Elman (RNNJ y RNNE, respectivamente) para la predicción del huevo diario producción en gallinas ponedoras comerciales. Los modelos se instalaron utilizando 4650 datos de 12 lotes seleccionados. Los modelos MP y LM dieron un buen ajuste a los datos, con valores de correlación superiores a 0,95 y que representan más del 95% de la variabilidad en la producción diaria de óvulos. Para el pronóstico de producción, MP fue una técnica con una precisión aceptable y menos variación. El modelo MP se recomienda como herramienta de ajuste y previsión de la curva diaria de producción de huevos en gallinas comerciales.

Pronóstico de la curva de producción de huevos con redes neuronales

ADDITIONAL KEYWORDS

Curve modeling.
Mathematical model.
Poultry farming.
Segmented polynomials.

SUMMARY

The comparison between the real egg production curve and the graph proposed by management guidelines, aims towards continuous performance evaluation. The objectives of this study was to compare the capacity of curve fitting daily egg production of Lokhorst (LM), neural network multilayer perceptron (MP) and Jordan and Elman recurrent neural network (RNNJ and RNNE, respectively) for the prediction of the daily egg production in commercial laying hens. The models were fitted using 4650 data from 12 selected batches. The MP and LM models gave good fitting to the data, with correlation values greater than 0.95 and accounting for more than 95% of the variability in daily egg production. For the production forecast, MP was a technique with acceptable accuracy and less variation. The MP model can be recommended as a tool for fit and forecast of daily egg production curve in commercial hens.

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INTRODUCTION

The administration of a livestock enterprise requires extensive knowledge of the production processes. The characterization of the components allows producers to identify the critical points, evaluate alternative solutions to the problems and most importantly, to make real-time decisions.

The comparison between the real egg production curve and the graph proposed by management guidelines, aims towards continuous performance evaluation. Usually, in the process of development and adaptation of the different types of models representing the commercial production curve laying hens it has been used productive information at weekly intervals. Some of common models used are the logistic functions (Adams & Bell 1980, p.937), polynomial functions (Bell & Adams 1992, p.448), exponential functions, segmented polynomials (Lokhorst 1996, p.838), nonlinear models (Savegnago et al. 2011, p.705; Galeano et al. 2013, p.270), linear mixed effect models (Wolc et al. 2011, p.30) and neural networks (Savegnago et al. 2011, p.705). These models are distinguished by trying to analyze the process of egg production, to describe the relation between the number of eggs and time of laying period (days), and to estimate future total production using partial records and projecting egg production. These models use as input variables egg production and time in weekly or daily periods, thus fit the curve and making short-term predictions. To achieve the adjustment it's necessary to estimate from 3 to 8 parameters, as is the case of mixed models. It has been shown that these modeling methodologies present disadvantages in the adjustment of the egg production curve, especially in the initial phase where it has an abrupt increase in the number of eggs in a short time, which makes the models estimate absurd values (Ahmad 2011, p.466; Savegnago et al. 2011, p.2977)

Several authors have demonstrated the advantages of the use of artificial neural networks in the adjustment, prognosis and prediction of data compared to other modeling techniques (Felipe et al. 2015, p.772; Ahmad 2011, p.463; Savegnago et al. 2011, p.705). These researchers made special emphasis on the use of multilayer perceptron (MP) network, because of its great capacity for data collection, flexibility and ease of adjustment. In addition, they mentioned MP capability to incorporate any type of data without satisfying the statistical assumptions (normal, homoscedasticity, independence, etc.) when the model is estimated. However, the most important feature is its ability to learn and restructure, making it a model that adapts constantly (Galeano & Cerón-Muñoz 2013, p. 3861; Rahimi & Behmanesh 2012, p.69).

Recurrent neural networks (RNNs) are computer models considered more powerful than MP and are distinguished by having at least one closed cycle of neuronal activation by the presence of feedback connections of a neuron to itself or between several neurons. These connections enable the system remember the previous state of certain neurons in the network. The input layer consists of two types of neurons, the first is the input information for the network (external patterns) and the second called context neurons, having the recurrent connections between different layers (output layer or hidden layer) (Galvan & Zaldívar 1997, p.506).

Jordan and Elman are the most popular recurrent networks (RNNJ and RNNE, respectively). In the RNNJ (Jordan 1990, p.112), the context neurons receive a connection from the output neurons and themselves and this connections having an associated parameter determining the sensitivity of these neurons to store the results of previous iterations (generally positive and less than 1). The RNNE (Elman 1990, p.179) proposed a model in which context neurons receive information from connections with neurons in the hidden layers of the network, whereby the number of context neurons in the input layer depends on the number of neurons in the hidden layer (Galvan & Zaldívar 1997, p.506).

This research was performed to compare the curve fitting capacity of the daily egg production of Lokhorst (LM), MP, RNNJ and RNNE models for the prediction of the daily egg production in commercial laying hens.

MATERIALS AND METHODS

Data were obtained from 12 commercial layer flocks in her first laying cycle, for 4650 data of daily egg production. The flocks evaluated began production between 19-23 weeks of age, with an average duration of the productive cycle of 54 weeks and a maximum duration of 70 weeks (90 weeks old). All egg production data was recorded daily in a database and was expressed as the number of eggs per day. During the production period, hens were housed in cages, ensuring 750 cm2 per bird. Hens were fed according to the dietary recommendations of each line. Water was supplied ad libitum, and the environmental conditions (temperature and humidity) were not controlled.

For fitting model, the variables (age and daily number of eggs) used were normalized in accordance with the method proposed by Savegnago (Savegnago et al. 2011, p.705) with equation 1:

$$y_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \qquad (1)$$

Where y_i is the new variable after the normalization process, x_i is the original variable, x_{min} is the minimum, x_{max} is the maximum value of the x_i variable.

$$y_i = \frac{m}{1 + a * r^{t_i}} - (b + c * t_i + d * t_i^{\,2}) + \varepsilon_i \qquad (2)$$

Where is the number eggs produced for the i^{th} day. Parameters *a* and *b* allow the model to adjust the hen-day egg production at the start of the laying period. The time period between the start of production and the peak of the curve is influenced by the *r* parameter. The weekly decline-rate production after the peak is determined by the value of parameter *c*. The slope of the final decrease is given by factor *d*. Variable t_i refers to the i^{th} age of the flock (days), and is the residual effect associated with the i^{th} time.

In the original model proposed by Lokhorst, the numerator of the first term was 100, as this is the maximum productive percentage that the flock can achieve. However, trying to fit the model to data from the number of eggs per day did not reach convergence; because of this, the value of 100 was replaced by the parameter *m* in the model. The value of *m* refers to the maximum value of eggs produced daily.

The MP, RNNJ and RNNE models was generated in the following form,

$$y_i = f\left(b_0 + \sum_{j=1}^{r} w_j \, f\left(b_{0j} + \sum_{i=1}^{n} w_{ij} \; x_i(t) + \sum_{i=1}^{n} v_{ij} \; c_i(t)\right)\right) \qquad (3)$$

Where denotes the vector of output values, *r* is the number of hidden neurons, and are the bias and denotes the value of intercept of the output neuron and intercept of the j^{th} hidden neuron, respectively. The term () is defined as a propagation function, where is added the product of the synaptic weight vector and the vector of input variables . In this work, input vector x is given by . The synaptic weight corresponding to the synapse at the j^{th} hidden neuron is defined , and is the activation function or transference. In the equation 3 el term is only present in RNNJ and RNNE models and is defined as context neurons, which contain the recurrent connections of the neuronal model.

Activation of the context neurons in *t* for RNNJ model was calculated,

$$c_i(t) = \varphi c_i(t-1) + \hat{y}_{i\,t-1} \qquad (4)$$

is the context neurons, for *i= 1, 2,… m*, with *m* equal to number of network outputs (*m=1*), is the associated parameter that usually takes a constant value and is the synaptic weight corresponding to the synapse starting at the j[th] hidden neuron.

Activation of the context neurons in *t* for RNNE model was calculated,

$$c_i(t) = a_i(t-1) \qquad (5)$$

Where are the activations of these neurons at time *t-1*.

For MP, RNNJ and RNNE, the activation function used in the input and hidden neurons was the sigmoid, as shown in equation 6, whereas in the output and context neuron was used as a linear activation function 7.

Sigmoid activation function

$$f(x) = \frac{1}{1+e^{-x}} \qquad (6)$$

Linear activation function

$$f(x) = x \qquad (7)$$

In order to fulfill the objective of adjusting the daily egg production curve, the MP structure was defined through previous trials comparing different combinations: number of productive days prior to the day (t_i), value of the learning ratio, value of the momentum parameter, and learning algorithms, and number of iterations in the network and number of hidden neurons. Finally, the network that offered the lowest error value was structured with three neurons in the input layer included information of day, number of eggs production in two previous days at the i^{th} day t_i (, with *n=3*), one hidden layer with five neurons and one neuron in the output layer corresponding to the number of eggs at i^{th} day. The backpropagation method was used like learning algorithm in MP model.

For the forecast of egg production, in addition to the criteria evaluated for the adjustment of the production curve in the MP model, we also evaluated the combinations between the number of production data needed to train the network (T) and the number of egg production values which the model should estimate (h). It was considered as a prediction line that the model estimated the production of the seven days following the number of eggs of the i^{th} day, so that the value of h was defined as 7. To define the number of days required for learning in the neuronal models (T), the production data were divided into three sets (at day 100, 200 and 300), so that by increasing the value of T the neural network had more data for training and learning.

The neural models were structured by a output neuron (number of eggs at i^{th} day), a hidden layer with 10 neurons, and the input layer with 6 neurons for MP model, that included information of number of day and production in five previous days at the i^{th} day t_i (, with *n=5*), and additionally the RNNE and RNNJ models had a layer with a context neurons.

The accuracy of the models was determined by Pearson's correlation between actual and predicted number of eggs, determination coefficient for each model was performed a linear regression analysis,

Table I. Results of accurate of the curve fitting of daily egg production in 12 flocks with the use of neural network multilayer perceptron (MP) and Lokhorst model (LM) (Resultados de la precisión de la adaptación de la curva de la producción diaria de huevos en 12 grupos con el uso de la red neuronal del Perceptrón multicapa (MP) y el modelo Lokhorst (LM)

Flock	n	MSE		MAD		MAPE		PC		R^2	
		MP	LM	MP	LM	MP (%)	LM (%)	MP	LM	MP	LM
1	161	11.3	10332.1	2.48	82.95	0.06	1.86	1.00	1.00	1.00	0.99
2	111	1509.3	3206.5	27.9	44.3	0.53	0.81	1.00	1.00	1.00	0.99
3	111	2149.9	4575.5	34.4	53.9	0.48	0.76	1.00	1.00	1.00	0.99
4	138	4503.0	31930.5	47.96	120.9	0.88	2.22	1.00	1.00	0.99	0.98
5	187	5248.7	38545.7	49.4	157.0	0.68	2.04	1.00	1.00	0.98	0.92
6	134	5649.9	18465.5	55.6	102.6	0.92	1.67	1.00	0.96	1.00	0.97
7	169	5808.5	20666.9	54	118.3	0.95	1.98	1.00	0.99	1.00	0.98
8	195	5907.5	63012.3	47.4	207.5	0.77	3.22	1.00	0.99	0.98	0.96
9	159	7923.7	24068.2	57.8	120.4	0.59	1.21	1.00	0.99	1.00	0.97
10	136	8554.8	17307.5	61.8	98.2	1.00	1.49	1.00	0.99	0.99	0.94
11	166	21252.5	98716.2	81.9	202.2	1.47	3.53	0.98	0.90	0.96	0.81
12	130	23035.4	40030.3	81.97	120.6	1.05	1.57	1.00	0.98	0.99	0.98
Mean	149.8	7629.6	30904.8	50.21	119.1	0.78	1.86	1.00	0.98	0.99	0.96
SD	27.39	7230.2	27214.3	21.92	50.5	0.35	0.84	0.01	0.03	0.01	0.05

Where n is the number of data used to validate models, MSE: mean square error, MAD: mean absolute deviation, MAPE: mean absolute percentage error, PC: Pearson´s correlation (statistically significant to $p<0.05$), R^2: determination coefficient and SD: standard deviation.

Table II. Mean absolute deviation (MAD) and mean square error (MSE) of neural network models used to predict the daily egg production (Desviación absoluta media (MAD) y error cuadrado medio (MSE) de los modelos de red neural utilizados para predecir la producción diaria de huevos).

T	L	MAD			MSE		
		RNNE	RNNJ	MP	RNNE	RNNJ	MP
100	1	96.1	38.5	61.7	13110.8	2275.7	4865.0
	2	54	27.8	58.6	3906.7	1188.2	4447.8
	3	58.1	55.6	59.4	4362.6	4122.9	4549.0
	4	26.9	140.6	41.1	1113.7	21707.6	2576.5
	mean	58.8±28.5	65.6±51.3	55.2±9.5	5623.5±5194.1	7323.6±9665.5	4109.6±1037.4
200	1	17.6	27.3	40.9	430.7	982.3	2096.9
	2	28.7	44.0	45.2	1167.5	2360.5	2497.1
	3	16.4	129.1	36.7	372.3	20605.2	1754.6
	4	77.5	115.1	45	6943.0	15774.1	2486.5
	mean	35.1±28.8	78.9±50.7	41.9±4.0	2228.4±3163.9	9930.5±9754.9	2208.8±355.5
300	1	85.8	54.69	50.8	9084.9	3251.0	3188.6
	2	100.9	68.16	63.2	11020.7	6072.2	4731.1
	3	110.6	92.27	69.5	13353.3	9637.7	5804.9
	4	73.5	27.75	66.8	5949.6	1115.8	5245.2
	mean	92.7±16.4	60.7±26.9	62.6±8.3	9852.2±3132.7	5019.2±3687.9	4742.4±1124.9

T: trained network days, L: number of model runs, RNNE: recurrent neural network of Elman, RNNJ: recurrent neural network of Jordan and MP: multilayer perceptron. Note: 7d forecasted and 6d neruronal input were used.

considering the number of eggs predicted by the model as the dependent variable and the number of eggs observed in each week as the independent variable. Mean square error (MSE), mean absolute deviation (MAD) and mean absolute percentage error (MAPE) were also used (equation 8, 9 and 10 respectively).

$$MSE = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|^2}{n} \qquad (8)$$

$$MAD = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n} \qquad (9)$$

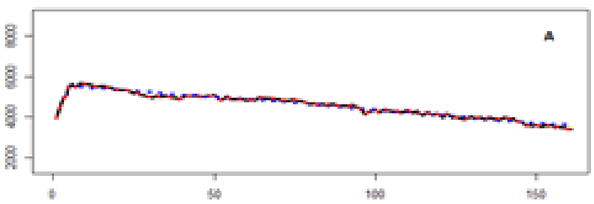
$$MAPE = \frac{\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right|}{n} x\ 100, \quad (y_i \neq 0) \qquad (10)$$

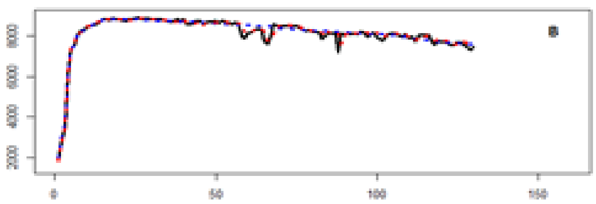
Where is the observed value at time i, is the estimated value, and n equals to the number of observations.

The data analysis were performed with the R program (R Core Time, 2016). The model MP was developed with the AMORE library (Castejon et al. 2014), the RSNNS library was used to develop the RNNJ, and RNNE models (Bergmeir & Benitez 2012, p.1).

RESULTS AND DISCUSSION

For the curve fitting, the productive information of 12 flocks were used to compare the ability of MP and LM models to fit the egg production curve. The flocks were ordered and numbered from 1 to 12 based on the value of MSE for MP, where the flock 1 being the lowest MSE and 12 the highest MSE **(Table I).** In test





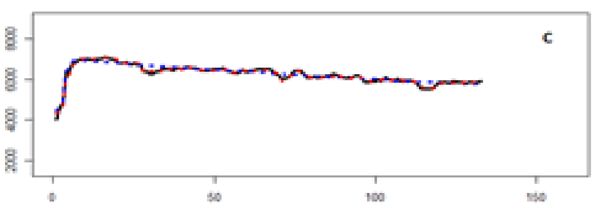


Figure 1. Data of daily egg production for validation set (——) and fitted using Lokhorst (-----) and multilayer perceptron (-----) models in the testing phase by 1, 2 and 3 flocks (A, B and C, respectively). The x and y axis are days and eggs number, respectively (Datos de la producción diaria de óvulos para el conjunto de validación (——) y equipados con modelos de lokhorst (-----) y multicapa Perceptrón (-----) en fase de ensayo por 1, 2 y 3 rebaños (A, B y C, respectivamente). El eje x e y es el número de días y huevos, respectivamente).

phase for MP and LM models were used 1797 data equivalent to 40% of the total information.

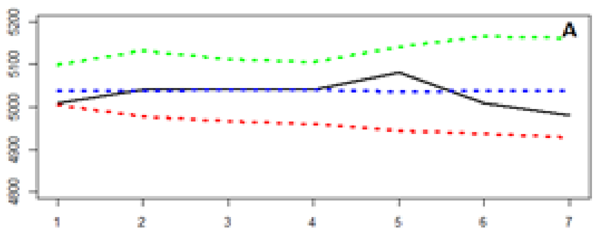
Both models provide acceptable adjustments for the production curve, with correlation values greater than 0.90 and reaching values of coefficient of determination greater than 0.92 in 96% of the 24 tests **(Table I)**. However, the MP network had better predictions to incur an average error of only 50 eggs/day of MAD. Similar results of correlation coefficients were reported by Savegnago et al. (2011, p.705), which compared MP with logistic model and found better performance by the neural network to fit the curve of weekly egg production.

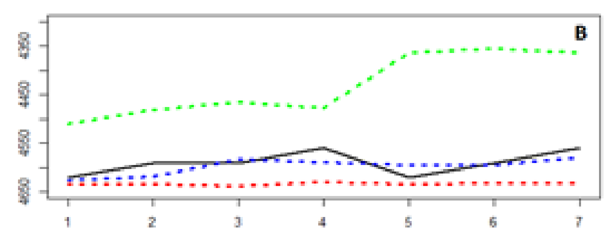
Another advantage of the networks was that the model LM had to estimate six parameters, and in order to do that seed values were needed (starting values). The selection of wrong initial values did not allow the start of the iterations and the model did not converge, so it became very tedious and slowed the adjustment process of LM.

MP has a setting closer to the changes presented in the production curve, while the LM does not **(Figure 1)**. It should be noted that although the three flocks have variations or fluctuations in production, the 12th has the strongest falls with average declines of 590 eggs by day and are not cyclical or are associated with any repetitive pattern that allows models to learn and reproduce these changes. These variations in production may be associated with environmental factors, heterogeneity of the hens to reach sexual maturity, disease in birds or other factors that directly or indirectly influence the productive response of the bird like management activities (Galeano et al. 2013, p.270). The neural model due to the ease of adjustment, the existence of GNU software and libraries for its programming, the efficiency and speed of its adjustment and the need for a few variables for its operation, can successfully replace the traditional mathematical and statistical models used for the adjustment of the egg production curve of layer hens (Ahmad 2011, p.473).

To evaluate the forecasting ability for predict the future production were compared MP, RNNE and RNNJ models. From the 12 flocks previously evaluated with MP and LM, the best adjustment curve was selected. However, the initial production phase (days 1 to 26) was not included in the data used to train and test the MP, RNNR and RNNJ models, because the MP as LM had higher estimation errors at this stage. This adjustment problem in the initial phase of the curve of egg production was reported by Shiv & Singh (2008, p.649), who showed that the models have difficulty adjusting the high and fast rate of increase in production in a short time.

In order to evaluate the predictive ability of the models and their stability, a prediction boundary was established from 7 days to the future and the networks were trained with three sets each containing an increasing number of data (T1: 100, T2: 200 , T3: 300). In each T value each model was executed 4 times, the estimated value was recorded and the prediction error (MAD and MSE) was obtained allowing the calculation of the standard deviation of the prediction errors as a criterion of stability of the models **(Table II)**. As for the increased the trained network days (T), one could expect that the neural networks with a greater number of learning data should have a better fit and that the MAD and MSE values should decrease. But as shown for the values of T=300, the models RNNE and MP increased their error value in regards to T=100 and T=200. This increase in the error at T = 300, can be associated with the decrease in the egg production values of 6% (220 eggs) on day 299 **(Figure 1, Table II)**. To understand what happened in model prediction it is necessary to introduce the concepts of precision and accuracy. The first is the measurement of the standard deviation of an estimation procedure and indicates the reproducibility of the results, and the second is expressed in terms of





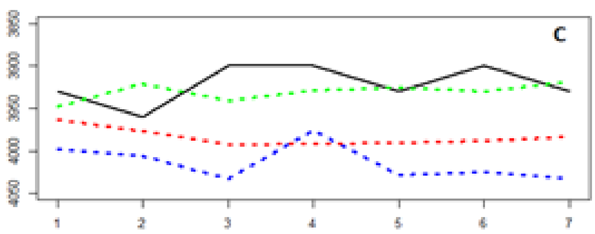


Figure 2. Daily egg production (y axis) for forecasting days (x axis) with recurrent neural network of Jordan (----) and Elman (----), multilayer perceptron (----) and observed data in flock 1 (——) at 100, 200 and 300 trained network days (A, B and C, respectively)(Producción diaria de huevos (eje y) para días de pronóstico (eje x) con red neural recurrente de Jordan () y Elman (), perceptrón multicapa () y datos observados en Flock 1 () a 100, 200 y 300 días de red entrenados (a, B y C, respectivamente)

error as the total distance between the estimated value and the actual value (Walther & Moore 2005, p.816). The MAD mean values in **Table II** show how the three models lack accuracy, but the standard deviations of the MAD values show that the PM model has higher precision. **Figure 2** shows the forecasting values of the models and shows how the prediction of the RNNE model is more adjusted to the real data when it was trained with 100 and 200 days in comparison with the other models. While the RNNJ model is the best fit when was trained with 300 days

The MP model is a technique with an acceptable accuracy, since its variation is less than the other models tested for each T; but it is not an exact estimation technique, because their predicted values differ from the expected value of eggs produced per day. However, the average error was of 54 eggs in three T, equivalent to an approximate deviation of 1.2% of production per day.

In general, the estimation of RNNE, RNNJ and MP in the forecasting process follows the trend of the training data, but as the production values change abruptly, it is difficult to correctly predict subsequent changes at point T. For this reason, it is necessary to implement other alternatives such as smoothing functions, used as input variables for longer periods of production, thus decreasing its variation. In addition, to include new input variables that help explain the changes in production. The MP model periods of production provide an acceptable fit in predicting the trend of production curve, but it is not an exact prediction technique.

CONCLUSIONS

The MP model is recommended as a tool for fit and forecast the curve of the daily egg production in commercial laying hens. To improve the predictive power of the model, it is necessary to identify the causes of variations in production from the inclusion of more input variables such as temperature, relative humidity, feed intake, nutrient intake, amount water ingested and management activities, among others. Also attempts to try longer periods of prediction (more than one week of production), and assess higher production intervals of a day as model input variable, with aims to reduce the variability in the input data and improve model accuracy. Future evaluation of alternative models were also proposed: the method of moving averages, exponential smoothing, segmented polynomials and generalized additive models, among others.

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