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Use of artificial neural networks to estimate production variables of broilers breeders in the production phase

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Abstract 1. Although the poultry industry uses state-of-the-art equipment and up-to-date services, in Brazil it generally makes decisions involving all its production variables based on purely subjective criteria. This paper reports the use of artificial neural networks to estimate performance in production birds belonging to a South Brazilian poultry farm.

2. Recorded data from 22 broiler production breeder flocks were obtained, from April, 1998 to December, 1999, which corresponded to 689 data lines of weekly recordings.

3. These data were processed by artificial neural networks using the software NeuroShell 2® version 4·0™ (Ward Systems Group®). The artificial neural network models generated were compared and selected based on their largest determination coefficient (R^2), lowest Mean Squared Error (MSE), as well as on a uniform scatter in the residual plots. The authors conclude that it is possible to explain the performance variables of production birds, with the use of artificial neural networks.

4. The method allows the decisions made by the technical staff to be based on objective, scientific criteria, allows simulations of the consequences related to these decisions, and reports the contribution of each variable to the variables under study.

INTRODUCTION

Although the poultry industry uses state-of-the-art equipment and up-to-date services, in Brazil it generally makes decisions involving all its production variables based on purely subjective criteria. Such important economic and social activities need objective criteria, based on a scientific approach combined with probabilistic predictions, providing support to improve flocks' productivity, and offering better product quality. Neural networks have been used for many applications: pattern classification and pattern recognition; prediction of financial indices such as currency exchange rates; optimisation of chemical processes; identification of cancerous cells; recognition of chromosomal abnormalities; detection of ventricular fibrillation (Cheng and Titterington, 1994).

Neural networks were inspired in the structure and functioning of biological neurones. Neural networks learn from patterns of interactions, without requiring a priori knowledge of relations between the variables under investigation. An artificial network works like biological neurones, each receiving one or more inputs and transforming the sums of those inputs into an output value that is transferred to other 'neurones', and so on successively. An artificial neural network is a set of processing units (or nodes) that are interconnected by a set of weights (analogous to synaptic connections in the nervous system) that allow both serial and parallel processing of information through the network (Astion and Wilding, 1992; Roush *et al.*, 1996). The neural network 'neurons' may receive excitatory or inhibitory inputs from other 'neurons' (Forsström and Dalton, 1995), and produce an output that is usually a non-linear function of the net input (Astion and Wilding, 1992).

Regarding its use in poultry science, Roush *et al.* (1996) studied the prediction of ascites in broilers using artificial neural networks, comparing diagnostics results with the incidence predicted by the neural net. The neural network was a three-layer back-propagation neural network with an input

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layer of 15 neurons (defining 15 physiological variables), a hidden layer of 16 neurons, and an output layer of 2 neurons (the presence or absence of ascites). According to them, the neural net correctly identified the presence or absence of ascites. This is another alternative to analyse binary data, beyond the logistic regression proposed by Kirby *et al.* (1997). Roush *et al.* (1997) returned to using the neural net as a probabilistic prediction of ascites in broilers, but based on minimally invasive inputs (physiological factors that do not require the death of the bird). The probabilistic neural network inputs were O2 concentration in the blood, body weight, electrocardiogram (ECG), hematocrit, S wave, and heart rate of individual birds. The network classified the input patterns into specific output categories (for example, ascites or no ascites). The conclusion was that the use of models developed with artificial neural networks may enhance the diagnosis of ascites in broilers. The results may be useful in choosing and developing broiler strains that do not have a propensity for ascites.

Broiler breeder females possess the inherent ability to grow rapidly (North and Bell, 1990). When fully fed during the growing period, they gain excessive weight and deposit too much internal fat for maximum egg production. The authors also conclude that a process of weight control must encompass the entire growing period; it cannot be delayed until just before egg production begins. It is also stated that it is important that male weights be kept within a specific range. If they get too fat, they may have foot and leg problems (such as arthritis), becoming less effective in reproduction. Most of the Brazilian industry use feeding tables (g/d in a specific age) supplied by the genetic companies. The authors believe these tables should be used carefully, because broiler lines are selected and tested abroad, often under different climatic, sanitary and management reality. Evidence of this is that the industry using these tables agrees it is often required to make changes, and relating them to the feed supplied, which is reformulated based on local environmental needs.

This paper aims to study the use of artificial neural networks to estimate performance – outputs (feed supplied per female per day, eggs to be laid in the subsequent week, etc.), on the basis of specified variables – inputs (age, season, temperature, air relative humidity, number of birds, etc.) in production birds belonging to a South Brazilian poultry farm.

We used a retrospective, longitudinal, analytical and observational approach, in which the models generated are suitable for evaluating the use of the technique.

MATERIALS AND METHODS

As this is a recent subject to poultry, the terms used in this paper are explained (according to Ward Systems Group, 1996).

Activation function: when the neuron values in the preceding layer are multiplied by the weights to a neuron in the succeeding layer, the products are summed. An activation function is the algorithm applied to this sum and the result is placed in the neuron in the succeeding layer.

Back-propagation architecture – Ward Networks: hidden layers in a neural network are known as feature detectors. Ward Systems Groups invented a back-propagation network architecture with three hidden layers, which was used in this experiment, because it offers three ways of viewing the data.

Epoch: is a complete pass through the network of the entire set of training patterns.

Input: is a variable that a network uses to make a classification or prediction.

Layer: is a grouping of slabs (a slab is a group of neurons) in a network. A layer may have multiple slabs.

Learning rate: each time a pattern is presented to the network, the weights leading to an output node are modified slightly during learning in the direction required to produce a smaller error the next time the same pattern is presented. The amount of weight modification is the learning rate times the error.

Link: is the connection or set of weights between the slabs or groups of neurons in a network. Each link can have an individual learning rate and momentum.

Momentum rate: determines the proportion of the last weight change that is added into new weight change.

Neuron: a basic building block of simulated neural networks which processes a number of input values to produce an output value.

Output: the value or values the network is trying to predict or the classification values if the network is classifying patterns.

Slab: a group of neurons.

Supervised feed forward learning: is a method of training a neural network by presenting it with the correct answers (outputs) during training, according to the input variables also presented during training.

Weights: as neurons pass values from one layer of the network to the next layer in back-propagation networks, the values are modified by a weight value in that link that represents connection strengths between neurons.

The data used in the mathematical analysis were obtained from 21 broiler breeder flocks' records belonging to a Southern Brazilian poultry farm, which produces broilers from a single genetic line

(Cobb), collected over the period between 26th April 1998 and 19th December 1999.

Scatter graphs from all the variables were produced, aiming to identify any outliers (biologically impossible data), that once identified were eliminated. The 21 flocks produced 990 data lines, from which 301 were eliminated because of inconsistencies in their records.

The data used, therefore, produced just 689 data lines: 552 for the learning set (80%) and 137 for the test set (20%). These data were related to weekly recordings of the following variables.

Age (ranging between 25 and 66 weeks old).

Season of the year (1 – Winter: 21st June to 20th September; 2 – Autumn: 21st March to 20th June; 3 – Spring: 21st September to 20th December; 4 – Summer: 21st December to 20th March). The seasons were coded according to their light incidence, obliging the software to give more importance to the highest temperatures.

Temperature (°C).
Air relative humidity – ARH (%).
Number of female birds in the flock.
Number of male birds in the flock.
Female's accumulated mortality percentage.
Male's accumulated mortality percentage.
Feed supplied per female per day during the week (g).
Feed supplied per male per day during the week (g).
Total number of eggs laid during the week.
Percentage of eggs laid (eggs laid in relation to the chickens).
Total number of hatching eggs produced during the week.
Fertility (percentage of hatching eggs in relation to eggs laid).
Eggs set during the week (eggs actually set into the incubator).
Percentage of eggs set (eggs set in relation to the eggs laid).
Total number of chicks produced during the week.
Hatchability.

The temperature and air relative humidity were not measured in the chicken house, but were obtained from the Ministry of Agriculture's 8th Meteorological District, located in the neighbouring town of Bento Gonçalves, RS, Brazil (4 km away from the farm).

In order to obtain the artificial neural networks, the software NeuroShell 2® version 4·0™ (Ward Systems Group®) was used. A back-propagation architecture (Ward Network), with supervised feed forward networks with three hidden layers and different activation functions was used to produce the artificial neural networks (Figure 1). The input layer (slab 1) used a linear scale function [−1, 1]. The first hidden layer, slab 2, used a Gaussian function. The second hidden layer, slab 3, used a hyperbolic tangent function and the third hidden layer, slab 4, used a Gaussian complement function. The output layer (slab 5) used an activation logistic function (sigmoid logistic). The links among neurons were adjusted for learning and momentum rates in 0·1 and the initial weights were between +0·3 and −0·3.

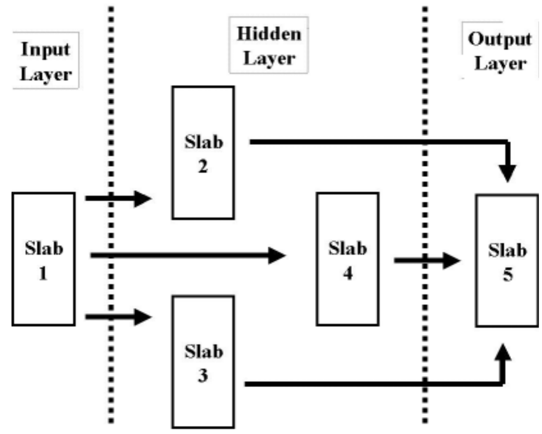


Figure 1. *Artificial neural network back-propagation architecture used in the experiment. Input = variable that a network used to make a classification or prediction; Layer = grouping of slabs; Link = connection between the slabs or groups of neurons in a network; Neuron = basic building block of simulated neural networks which processes a number of input values to produce an output value; Output = value or values the network is trying to predict; Slab = group of neurons.*

The training data-set was partitioned into a learning set (80% – 552 lines) and a randomly chosen test set (20% – 137 lines). After an input pattern was presented to the first layer of neurons, it was then propagated through each succeeding layer, until an output was generated. This output pattern was compared with the actual output, and an error signal was calculated for each output. This error signal was transmitted backwards across the neural network (back-propagation). The connection weights were appropriately updated, in order to decrease the error in the network. As learning proceeded, the error between the input and output decreased and the neural network 'learned' the pattern of data (Forsström and Dalton, 1995).

In fact, there was the possibility of building 34 468 different models, but embracing all the possible logical combinations, it would take more than 4 years to complete the experiment execution, at 8 h per day and 15 min per model. So, the approach was to use veterinary knowledge to choose the variables (inputs) that could have influence on the outputs we wanted to predict and test then.

The artificial neural networks models generated were compared and the best were selected, based on their largest determination coefficient, (R^2), lowest mean square error (MSE), as well as on an uniform scatter in the residual plots.

RESULTS AND DISCUSSION

With the data available, it was possible to build and test 248 models for 16 output variables. These are listed in Table 1.

As an example of all the procedures used, Table 2 presents the network constructs for the 15 models built to predict the output 'Eggs to be laid in the subsequent week'. The model chosen (best) to be used for the simulation was model number 15, because it reported the lowest MSE and the largest R^2, and also because this net presented uniform scatter in the residual plots.

Table 3, shows the contributions in percentage of the different inputs used to estimate the outputs. This is of importance in understanding what is interfering with the variable to be predicted. With this number available, poultry professionals can evaluate the data, propose pertinent corrections. and focus on the biggest interfering variables. This method is a tool for process management, specifically in this case, of the production phase. Some inputs may be modified, others like season of the year, age and accumulated mortality are unchangeable. However, it is possible to change environmental temperature, ARH and feed supplied, and by doing so aim to improve the number of eggs to be produced in the subsequent week. Decisions taken to improve the process will, of course, have their efficacy measured when the new model incorporates the modifications. Considering the contribution of each input that produced a model predicting 'Eggs to be laid in the subsequent week' as output, the number of eggs laid during the week has a major contribution over the number of eggs to be laid in the subsequent

Table 1. *Outputs (variables to be predicted) and number of models (nets) generated*

Output (variable to be predicted)	Number of models
Female accumulated mortality percentage	6
Male accumulated mortality percentage	6
Feed supplied per female per day during the week (g)	7
Feed supplied per male per day during the week (g)	7
Total number of eggs laid during the week	10
Total number of eggs to be laid in the subsequent week	15
Percentage of eggs laid (eggs laid in relation to the chickens)	15
Total number of hatching eggs produced during the week	15
Total number of hatching eggs to be produced in the subsequent week	17
Fertility (percentage of hatching eggs in relation to eggs laid)	17
Eggs set during the week (eggs actually set into the incubator)	17
Eggs to be set in the subsequent week	22
Percentage of eggs set (eggs set in relation to the eggs laid)	22
Total number of chicks produced during the week	22
Total number of chicks to be produced in the subsequent week	25
Hatchability	25

Table 2. *Information about the artificial neural networks built to predict the 'Eggs to be laid in the subsequent week' output*

Models	Ninput	Nhidden	Noutput	Epochs	MSE	R^2
01	1	11	16	136	6 461 762·513	75·13
02	2	11	16	165	5 340 537·943	79·45
03	3	11	16	104	6 266 087·446	75·88
04	6	9	13	112	1 264 896·283	95·13
05	4	10	12	130	1 453 383·485	94·41
06	5	11	12	107	1 478 954·604	94·31
07	6	11	12	182	1 262 520·287	95·14
08	8	11	12	167	1 037 144·494	96·01
09	10	11	12	150	712 064·196	97·26
10	5	11	12	107	1 196 222·567	95·40
11	11	11	11	75	506 702·564	98·05
12	2	10	11	163	582 490·724	97·76
13	5	10	11	258	457 969·438	98·24
14	4	10	11	111	611 518·886	97·65
15	8	11	11	258	406 542·258	98·25

Ninput = number of neurons in the input layer; Nhidden = number of neurons in the hidden layer; Noutput = number of neurones in the output layer; Epochs = calculation loops to test the artificial neural network; MSE = mean squared error; R^2 = multiple determination coefficient.

Table 3. *Contributions in percentage of the different inputs used to estimate the outputs (in this table there are only the chosen models).*

Inputs	Outputs						
	Females accumulated mortality (%)	Males accumulated mortality (%)	Standards			Predictions	
			Total number of eggs laid during the week	Feed supplied per female per day during the week (g)	Feed supplied per male per day during the week (g)	Eggs to be laid in the subsequent week	Chicks to be produced in the subsequent week
Age (weeks)	37·70	34·89	41·79	39·73	17·04	16·06	10·64
Season	19·26	13·55	9·18	10·82	18·12	7·45	5·29
Temperature (°C)	11·32	15·02	7·99	8·27	12·77	9·25	7·36
ARH (%)	8·11	13·94	6·08	6·45	14·82	8·77	9·07
Number of females	23·61	–	16·20	14·97	–	11·74	8·29
Number of males	–	22·60	–	–	17·88	–	7·07
Female's accumulated mortality (actual)	–	–	18·76	19·76	–	7·33	4·65
Male's accumulated mortality (actual)	–	–	–	–	19·37	–	7·11
Feed supplied per female per day (actual)	–	–	–	–	–	11·05	10·18
Feed supplied per male per day (actual)	–	–	–	–	–	–	11·64
Total number of eggs laid during the week (actual)	–	–	–	–	–	28·35	–
Eggs set during the week (actual)	–	–	–	–	–		18·70

week (28·35%). Other factors such as age, number of females in the flock and feed supplied per female are less important determinants. Environmental temperature, air relative humidity, season of the year and female accumulated mortality were much less important.

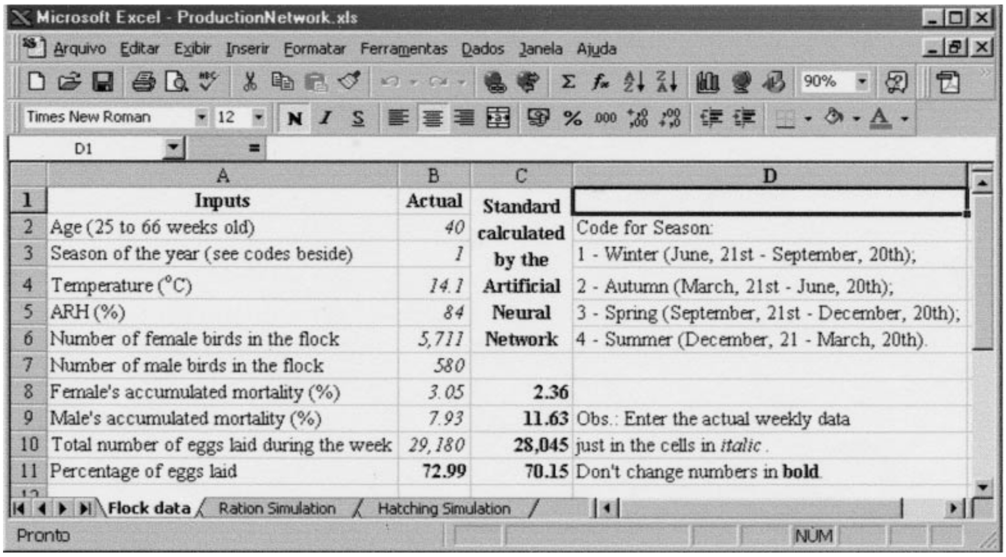
For the output 'Expected accumulated female mortality for the week', age and number of females in the flock are the major factors, whereas the environmental temperature and the ARH have smaller but similar contributions. However, as it is not practicable to change age, the season of the year or number of females, then environmental temperature and ARH are the only inputs that can be manipulated, in order to affect mortality. In the model generated for female accumulated mortality, 19·43% of the output is influenced by the variables subject *in totum*, or at least partially, to human manipulation.

The final results of an artificial neural network model chosen can be put in Excel® software worksheets, which are shown in Figures 2, 3 and 4. These three worksheets are interconnected, so the information typed in the first worksheet (Figure 2) is used in the subsequent worksheets (Figures 3 and 4).

In Figure 2, the weekly collection of the flock data for birds at 40 weeks of age is the example. In the worksheet, the number '40' is entered into the line 'Age', and the season number (1 to 4) in the line 'Season', and appropriate values are entered in each of following input lines, finally arriving at the predicted value at the line 'Total number of eggs laid during the week' (up to here the numbers are in italics). All values entered up to this point cannot be modified, as they are flock characteristics. So, in the column 'Standard calculated by the Artificial Neural Network', the flock performance can be compared with the company standard.

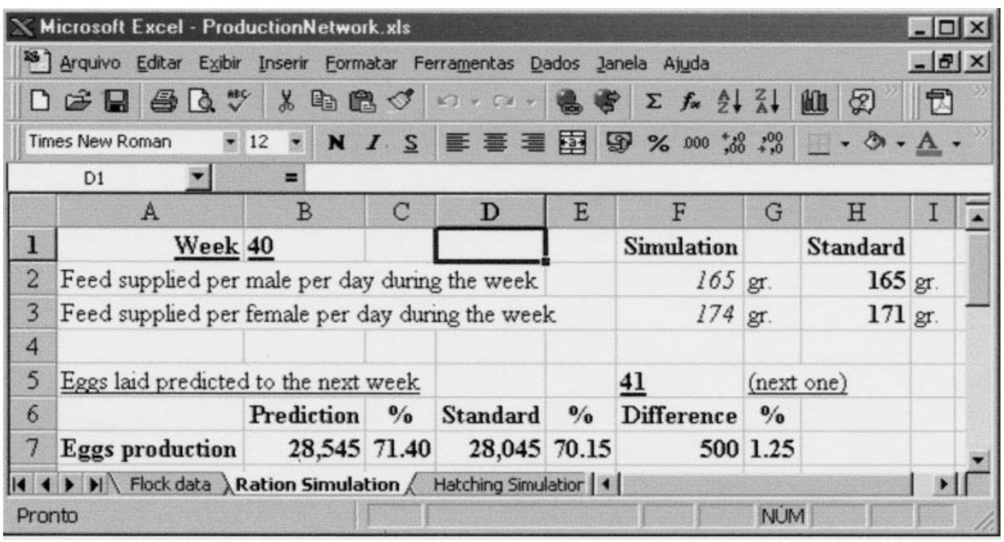
In Figure 3, 'Feed supplied per female per day during the week' can be modified, simulating what will happen to the following week's (week 41) egg production. The user enters the amount of feed to be supplied to the females in the appropriate cell. Automatically, the model indicates how much feed must be supplied per female in the week 40th in order for the flock to reach the intended egg production when week 41 begins.

In the column 'Standard', 28 045, is a value linked to a production standard that was also calculated by the artificial neural network (from age, season, temperature, ARH, number of females and mortality data). The cell that expresses the difference between the simulation results and the company's standard serves as a guide for deciding on a smaller or greater amount of feed to be supplied during the simulation process. In this example, if 174 g per bird per day of feed are supplied, egg production in the next week will be 28 545 eggs, which is 1·25% above the company's standard for week 41. As guidance, the worksheet also calculates the amount of feed to be supplied in the column 'Standard': 171 g (a dependent model derived



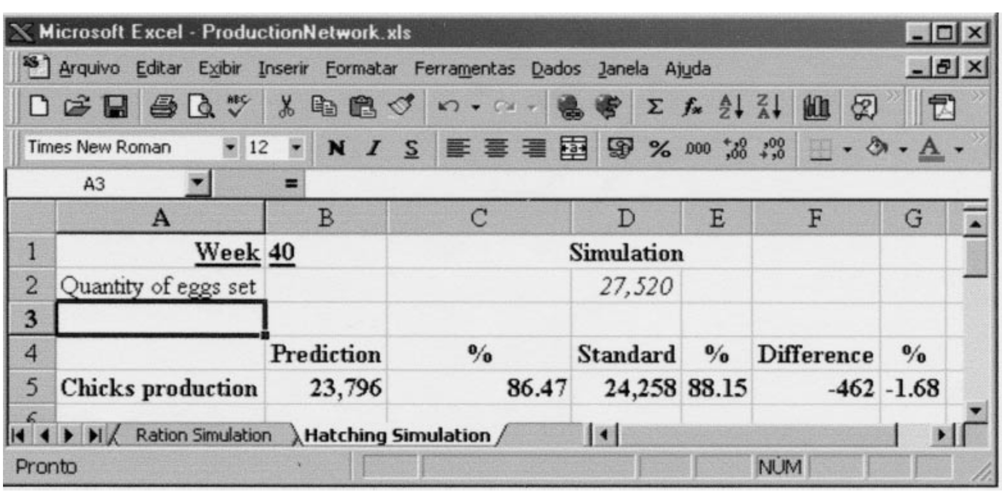
	A	B	C	D
1	**Inputs**	**Actual**	**Standard calculated by the Artificial Neural Network**	
2	Age (25 to 66 weeks old)	*40*		Code for Season:
3	Season of the year (see codes beside)	*1*		1 - Winter (June, 21st - September, 20th);
4	Temperature (°C)	*14.1*		2 - Autumn (March, 21st - June, 20th);
5	ARH (%)	*84*		3 - Spring (September, 21st - December, 20th);
6	Number of female birds in the flock	*5,711*		4 - Summer (December, 21 - March, 20th).
7	Number of male birds in the flock	*580*		
8	Female's accumulated mortality (%)	*3.05*	**2.36**	
9	Male's accumulated mortality (%)	*7.93*	**11.63**	Obs.: Enter the actual weekly data
10	Total number of eggs laid during the week	*29,180*	**28,045**	just in the cells in *italic*.
11	Percentage of eggs laid	**72.99**	**70.15**	Don't change numbers in **bold**.

Figure 2. *Electronic worksheet to verify the flocks' performance.*



	A	B	C	D	E	F	G	H	I
1	**Week**	**40**				**Simulation**		**Standard**	
2	Feed supplied per male per day during the week					*165*	gr.	**165**	gr.
3	Feed supplied per female per day during the week					*174*	gr.	**171**	gr.
4									
5	Eggs laid predicted to the next week					**41**	(next one)		
6		**Prediction**	**%**	**Standard**	**%**	**Difference**	**%**		
7	**Eggs production**	**28,545**	**71.40**	**28,045**	**70.15**	**500**	**1.25**		

Figure 3. *Electronic worksheet for simulating the subsequent week's egg laying, according to feed supplied per day to the females during the week.*



	A	B	C	D	E	F	G
1	**Week**	**40**		**Simulation**			
2	Quantity of eggs set			*27,520*			
3							
4		**Prediction**	**%**	**Standard**	**%**	**Difference**	**%**
5	**Chicks production**	**23,796**	**86.47**	**24,258**	**88.15**	**-462**	**-1.68**

Figure 4. *Electronic worksheet for the simulation of the number of chicks hatched from a given number of eggs set.*

from age, season, temperature, ARH, number of females and mortality).

When models are calculated by artificial neural networks and are placed in an electronic worksheet, the user can simulate the amount of feed necessary for the birds, with the objective that the difference between the production standard and the number the birds actually lay should be as small as possible, and thus prevent the birds' performance being depressed by any excess or lack of feed supplied.

In another worksheet (Figure 4), the user can simulate the number of chicks hatched from eggs set. In the line 'Quantity of eggs set', 27 520 eggs are entered and the worksheet calculates the number of chicks that will hatch (line 'Chick production': 23 796), derived from a dependent model of age, season of the year, temperature, ARH, number of birds, mortality, feed supplied and number of eggs set.

From the 990 data lines, 301 had to be eliminated because of inconsistent recordings. It is also important to point out that relevant data for the modelling, such as: pharmacological treatments, feed formulation, vaccinations, laboratory monitoring, management techniques, necropsy findings, houses' inner temperature, etc. were not systematically recorded by the company in any of the flocks studied, and so could not be incorporated in the models.

The recording mistakes, and the absence of important data suggest that, in the present stage of breeders' production management, the company's existing data are not being adequately analysed.

Outputs and inputs combinations were identified using veterinary knowledge and time available. Other combinations could have been used, but would be dependent on the answers required.

We believe that the generated models can be used effectively only by the poultry company where the study is carried out. In further work, a prospective field study should be performed, to test the validity of the models generated.

In conclusion, one can explain and model performance variables from breeder birds in a poultry farm, through the use of artificial neural networks. The method allows decision making by the technical staff for different production flocks to be based on scientifically obtained, objective criteria. Furthermore, this method allows the simulation of consequences following these decisions, also providing the contribution percentage from each input to the poultry production variables under study.

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