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REGULAR ARTICLES

Comparative assessments of multivariate nonlinear fuzzy regression techniques for egg production curve

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Abstract

The modelling process of egg production curves, where environmental and genetic factors are highly effective, is quite complex and difficult. In particular, the limitations of measurement and the errors encountered during the measurement process may cause uncertainty in the egg production process. In this study, multivariate nonlinear fuzzy regression analysis was used by configuring neural networks and least squares support vector machines in order to express the uncertainty in the system structure during the egg production process. This method was used to obtain the predicted values for egg production in the fuzzy frame. In the study, two different data sets were used which were measured for egg performance and egg weight variables in daily and weekly time periods. Multivariate nonlinear fuzzy regression analysis results were compared with both the observed values and the multivariate classical regression analysis results. Results of analysis show that multivariate nonlinear fuzzy regression analysis with neural networks is more successful than other methods and can be used as an alternative to classical methods in poultry farming.

Keywords Nonlinear fuzzy regression · Artificial neural networks · Least squares support vector machines · Egg production curve · Nonlinear modelling

Introduction

Modelling of egg production process in laying hens and estimating the egg production curves are the most important parts to evaluate productivity and make economic decisions (Savegnago et al. 2011; Mehri 2013). In order to determine the effects of poultry nutrition and breeding on egg production and to examine how the egg production curve changes over time, analysis can be done by using nonlinear functions. In the modelling of egg production process, various model structures have been developed to represent the production cycle of laying hens on individual or herd basis. Some of these models are as follows: Narushin- Takma, Adams- Bell, Lokhorst, Minder- McMillian, Lojistic-Curvilinear, Compartmental, Wood, McNally (McMillan 1981, Gavora et al. 1982; Fialho and Ledur 1997; Grossman et al. 2000; Narushin and Takma 2003; Narinc et al. 2014).

In the egg production process, the data has a curvilinear structure. Modelling this nonlinear structure, where environmental and genetic factors are highly effective, is quite complex and difficult. In particular, the combination of the limitations of measurement and the errors encountered during the measurement process may cause some uncertainty in the egg production process. Classical mathematical methods may not produce satisfactory results due to the fuzziness of information and environmental factors in systems including uncertainty. Today, various approaches to fuzzy modelling have been developed in order to express the uncertainty of the system structure (Türkşen 2015). One of these approaches is nonlinear fuzzy regression (NFR) analysis.

NFR is a very powerful modelling tool for applied science. In particular, it provides important contributions to researchers in cases where the relationships between variables are uncertain and data structure is nonlinear. The NFR model is used to obtain the prediction interval for the observation values of the dependent variable(s). For the purpose of defining functional relationships between variables, artificial intelligence-based

This study is derived from the PhD thesis titled "Analysis of Agricultural Data with Multivariate Nonlinear Fuzzy Regression Method".

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methods such as neural networks (NN) and least squares support vector machines (LSSVMs) can be preferred for NFR analysis in the process of obtaining fuzzy outputs. NN and LSSVM methods, which are important components of machine learning concept, can be used to construct NFR. NN and LSSVM are widely used in the modelling of nonlinear data structures, especially in the solution of prediction problems (Savegnago et al. 2011; Gorgulu and Akilli 2018).

Nonlinear fuzzy regression analysis is a relatively new method in poultry breeding. As a result of the literature review, there is no scientific study in the field of poultry. When the NFR studies in the applied sciences are examined, it is seen that there are various publications in which the data structure is in time series form or in a curvilinear form, similar to the egg production curve (Xu and Khoshgoftaar 2001; Lin and Pai 2010; Lin et al. 2013; He et al. 2016; He et al. 2018). In the study of artificial intelligence methods for modelling nonlinear data structures in poultry husbandry field, various neural network models (Roush et al. 2006; Ahmadi and Golian 2008; Ahmad 2009; Ahmad 2011; Kaewtapee et al. 2011; Savegnago et al. 2011; Wang et al. 2012; Semsarian et al. 2013; Safari-Aliqiarloo et al. 2017) and the least squares support vector machine method (Gorgulu and Akilli 2018) can be seen as a subject of highly successful applications. However, there are no MFNR studies on egg production curve in the literature.

In this study, multivariate nonlinear fuzzy regression analysis (MNFR) was used to obtain fuzzy prediction intervals of egg performance (EP) and egg weight (EW) variables. In the MNFR analysis, the input and output were determined as crisp and fuzzy number, respectively. In this context, MNFR analysis is structured as integrated with NN and LSSVM. The results were evaluated comparatively with the results of classical regression analysis and the observation values.

Materials and methods

Data source

In this study, two data sets from two strains of 100 layer hens were used. The first data set contained the first strain's daily per cent hen/day EP and EW (gr) over 70 weeks' period of egg laying, starting at 20 weeks of age and finishing at 90 weeks of age. The second data set contained the second strain's weekly per cent hen/day EP and EW (gr) over the same period. Eggs were collected on 1 day/week and 7 days/week for the first and second data sets, respectively. Data sets recorded as daily and weekly were analysed separately on the basis of the backpropagation algorithms and radial basis function (RBF) kernel function's parameters used. The training data set of NN and LSSVM was determined randomly with 60%, respectively, for both variables. Daily and weekly data sets from 100 layer hens were collected from a commercial egg production farm located in Izmir, Turkey. The analyses were performed using the Matlab (R2016a) program.

The accuracy of models was calculated using the mean square error (MSE), mean absolute percentage error (MAPE) and average absolute error (AAE). AAE^{+}, AAE^{-} and AAE^{c} indicate how close the upper limit, lower limit and centre of the predicted fuzzy output is to observed value of output, respectively. AA^{w} describes how wide is the interval for a given h-level. AAEs are given as numerical results of change in the prediction interval due to increase and decrease in h-level. The equations of the error criteria used in the study are given in Table 1.

Classical nonlinear regression

In this study, McNally model is discussed within the scope of multivariate classical nonlinear regression analysis. The mathematical representation of nonlinear model is represented by Eq. 1 (McNally 1971; LóPez 2008).

$$y_{\mathrm{t}} = \mathrm{at}^{\mathrm{b}}\mathrm{e}^{\left(-\mathrm{ct}+\mathrm{dt}^{0.5}\right)} \tag{1}$$

In order to perform multivariate nonlinear regression analysis in the Matlab program, the logarithm of both sides was taken in the equation. Thus, the model is transformed into linear form. Where y_{t} is egg production rate at t days of laying; a, b, c and d are for parameters that define the scale and shape of the curve. Parameters were estimated by Levenberg–Marquardt iteration algorithm. Convergence criterion was determined as 1.0×10^{-8}.

Multivariate nonlinear fuzzy regression based on neural network (MNFR-NN)

The multivariate nonlinear fuzzy regression based on neural network (MNFR-NN) was used to predict the daily and

Table 1 Statistical error criteria

Statistical error criteria	Equation
Mean square error (MSE)	$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2$
Mean absolute percentage error (MAPE)	$\mathrm{MAPE} = \left(\frac{100}{n}\right)\sum_{i=1}^{n}\left\lvert\frac{(y_i-\widehat{y}_i)}{y_i}\right\rvert$
Average absolute error (AAE)	$\mathrm{AAE}^{*} = \frac{1}{n}\sum_{i=1}^{n}\left\lvert y_i - [\widehat{y}(x_i)]_h^{*}\right\rvert$
	$\mathrm{AA}^{\mathrm{w}} = \frac{2}{n}\sum_{i=1}^{n}\left\lvert f^{w}(x_i)\right\rvert$

*Associated with upper bound (+), lower bound (−) and centre (c) weekly egg performance and egg weight as multivariates. In the MNFR analysis, a multilayer perceptron (MLP) was used to estimate the lower and upper limits of the fuzzy prediction interval. Backpropagation learning algorithm was used in MLP analysis. In the process of NFR-NN analysis, firstly, triangular fuzzy numbers were obtained for the dependent variables, and then fuzzy prediction intervals were calculated for different h-levels. Within the scope of the study, the spread and limit values of the observations of both dependent variables for NFR-NN were calculated according to the method proposed by Xu and Khoshgoftaar (2001). Spread values were obtained separately based on their mean and standard deviation of each dependent variable.

When symmetrical triangular membership functions are applied to nonlinear fuzzy regression, the predicted values for EP and EW are expressed as fuzzy numbers of $\widehat{Y}(x_i) = (f^c(x_i), f^w(x_i))$. $\widehat{Y}(x_i)$ is defined as a fuzzy number, which is an estimate of the y_i dependent variable. $f^c(x_i)$ and $f^w(x_i)$ are the centre and the spread of $\widehat{Y}(x_i)$, respectively. The h-level set of EP and EW is calculated by Eq. 2 ($h \epsilon (0, 1]$). The selection of a proper value of h-level is very important in fuzzy regression analysis because it provides the distribution of fuzzy parameters. In this study, fuzzy prediction interval was examined at five different h-levels as 0.1, 0.3, 0.5, 0.7 and 0.9.

$$\left[\widehat{Y}(x_i)\right]_h = [f^c(x_i) - (1-h) f^w(x_i), f^c(x_i) + (1-h) f^w(x_i)] \quad (2)$$

In the framework of the method proposed by Xu and Khoshgoftaar (2001), information on the neural network architecture and training parameters used to obtain the lower and upper limit values of the fuzzy prediction interval are given in Table 2. The optimal structure of the neural network was investigated in 10 different backpropagation algorithms, in two different activation functions, 1 to 3 layers, 3–20 neurons, and in the different values of learning parameters. The neural network architecture was optimized by examining the training and test errors in order to investigate the overfitting and underfitting problems.

Table 2 Summary of NN Structure for EP and EW

NN structure	Descriptions
Model	Multilayer perceptron
Connections	Feed-forward
Layer	1–3
Input node	1
Hidden node	3–20
Output node	2
Activation function	Tan-Sig, Log-Sig
Training parameters	Descriptions
Mode	Supervised
Algorithms	Backpropagation*
Weight updates	Each epoch
Learning rate	0.01
Momentum coefficient	0.95

*Bayesian regularization (BR), Levenberg-Marquardt (LM), Scaled Conjugate Gradient (SCG), Gradient Descent (GD), Gradient Descent with Momentum (GDM), Gradient Descent with Momentum and Adaptive Learning Rate (GDX), Conjugate Gradient Backpropagation with Fletcher-Reeves Updates (CGF), Conjugate Gradient Backpropagation with Powell-Beale Restarts (CGB), Brayde Fletcher Gold Farlo Shanno Quasi Newton Backpropagation (BFG) and One Step Secant Algorithm (OSS)

Multivariate nonlinear fuzzy regression based on least squares support vector machine

The LSSVM is the second method for configuring the MNFR and was used to predict the daily and weekly egg performance and egg weight as multivariate. Within the scope of the study, the method proposed by Hong and Hwang (2006) was used to perform multivariate nonlinear fuzzy regression based on least squares support vector machine (MNFR-LSSVM) analysis (Hong and Hwang 2003; Hong et al. 2006). The proposed model and convex optimization problem are given in Eqs. 3 and 4, respectively. The proposed model and convex optimization problem are given in Eqs. 3 and 4, respectively. Within the framework of the proposed method, the Lagrange function, which is located in Eq. 5, is created to solve the problem and results are obtained through a solution system called optimal conditions. In this study, triangular fuzzy numbers are used for MNFR-LSSVM analysis. X_i and Y_i represent the input and output variables, respectively, and their mathematical representations in the form of triangular fuzzy numbers are given as follows: $X_i = ((m_{Xi1}, \alpha_{Xi1}, \beta_{Xi1}), \ldots, (m_{Xid}, \alpha_{Xid}, \beta_{Xid})), Y_i = (m_{Yi}, \alpha_{Yi}, \beta_{Yi})$, $m_{Xi} = (m_{Xi1}, \ldots, m_{Xid})$, $\alpha_{Xi} = (\alpha_{Xi1}, \ldots, \alpha_{Xid})$, $\beta_{Xi} = (\beta_{Xi1}, \ldots, , \beta_{Xid})$.

$$Y(X) = \langle w, X \rangle + B = (\langle w, m_X \rangle + m_B, \langle |w|, \alpha_X \rangle + \alpha_B, \langle |w| \beta_X \rangle + \beta_B) \quad (3)$$

$$min \frac{1}{2} \|w\|^2 + \frac{C}{2} \sum_{k=1}^{3} \sum_{i=1}^{l} e_{ki}^2 \quad (4)$$

$$\begin{aligned} L = \frac{1}{2} \|w\|^2 + \frac{C}{2} \sum_{k=1}^{3} \sum_{i=1}^{l} e_{ki}^2 + \sum_{i=1}^{l} \alpha_{1i} (e_{1i} - m_{Y_l}) + \langle \sqsupseteq, m_{X_l} \rangle + m_B) \\ - \sum_{i=1}^{l} \alpha_{2i} \left(e_{2i} - \left(m_{Y_l} - \alpha_{Y_l} \right) + \langle w, m_{X_l} \rangle + m_B - \langle |w|, \alpha_{X_l} \rangle - \alpha_B \right)) \\ - \sum_{i=1}^{l} \alpha_{3i} \left(e_{3i} - \left(m_{Y_l} - \beta_{Y_l} \right) + \langle w, m_{X_l} \rangle + m_B + \left\langle |w|, \beta_{X_l} \right\rangle + \beta_B \right)) \end{aligned} \quad (5)$$

Table 3 MSE and MAPE results of multivariate classical nonlinear regression

Data set	Variable	Parameter	Parameter estimation	Standard error	Statistical error criteria	
					MSE	MAPE
Daily	EP	a	3.5363	0.0096	1.8482	1.3365
		b	0.3466	0.0069		
		c	− 0.0005	0.000074		
		d	− 0.0538	0.0031		
	EW	a	3.6526	0.0047	0.2712	0.6255
		b	0.1117	0.0034		
		c	− 0.0001	3.6839		
		d	− 0.0042	0.0015		
Weekly	EP	a	4.120	0.0326	6.2872	2.3776
		b	0.711	0.0435		
		c	0.008	0.0026		
		d	− 0.409	0.0459		
	EW	a	3.765	0.0096	0.2236	0.5664
		b	0.234	0.0128		
		c	0.003	0.0008		
		d	− 0.096	0.0135		

When the method proposed by Hong and Hwang (2006) is applied to the data set, the nonlinear estimation value for the dependent variable ($Y(X_q)$) is obtained on the X_q data. The mathematical representation of this situation is given in Eq. 6.

$$\widehat{Y}(X_q) = \left(\left\langle w^{\Phi}, (m_{X_q})\right\rangle + m_B, \left\langle |w^{\Phi}|, \alpha^{\Phi}_{X_q}\right\rangle + \alpha_B, \left\langle |w^{\Phi}|, \beta^{\Phi}_{X_q}\right\rangle + \beta_B\right) \quad (6)$$

$$K\left(x_i, x_j\right) = e^{-\frac{\|x_i - x_j\|^2}{\sigma^2}} \quad (7)$$

In this study, RBF kernel function is used. The mathematical representation of the RBF kernel function is given in Eq. 7. Here, σ^2 is defined as variance. MNFR-LSSVM is examined in different parameter combinations. The parameter σ is determined as “10, 30, 50, 70 and 90”; parameter γ is determined as “0.1, 0.3, 0.5, 0.7 and 0.9” for RBF kernel function.

Results and discussion

Table 3 shows the parameter estimation values and standard error values obtained by multivariate classical nonlinear regression analysis for daily and weekly measured data. According to these values, the model used in the multivariate classical nonlinear regression analysis seems to have a good fitting. Figure 1 shows the observed values of the daily (a) and weekly (b) measured EP and EW variables and graphical representations on the same plane for the estimation values. The results of the analysis show that the curves of actual and predicted values are very close to each other in both daily and weekly data. At the same time, it was determined that the model used in the analyses predicted the peaks of the curves quite successfully. The most successful prediction values for

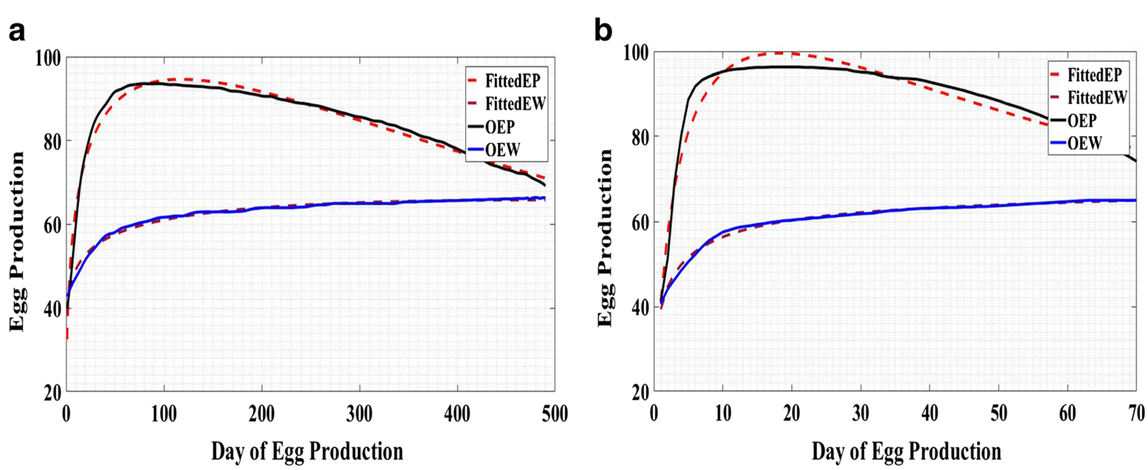

Fig. 1 Fitted curves for daily (**a**) and weekly (**b**) EP and EW using multivariate classical nonlinear regression. OEP, observed egg performance; OEW, observed egg weight

Table 4 MSE and MAPE results of MNFR-NN

Set	Variable	Activation functions	MSE		MAPE	
			Test set	Validation set	Test set	Validation set
Daily	EP	TanSig	0.0109	0.0109	0.0991	0.0946
	EW		0.0038	0.0041	0.0754	0.0710
	EP	LogSig	0.0138	0.0138	0.1119	0.1119
	EW		0.0111	0.0107	0.1235	0.1162
Weekly	EP	TanSig	0.0898	0.0660	0.2622	0.1970
	EW		0.0047	0.0044	0.0932	0.0833
	EP	LogSig	0.3369	0.0853	0.4186	0.2377
	EW		0.0089	0.0098	0.1104	0.1054

EP and EW were obtained by MNFR, which is integrated with structured neural network architecture with the BR algorithm and TanSig activation function. In MNFR analysis, the most appropriate h-level was determined as 0.7. The related numerical results are given in Table 4.

The graphical representations in Figs. 2 and 3 are given for the BR algorithm at $h = 0.7$. Accordingly, in the case of h-level 0.7, the EP curve and the EW curve exhibit the typical appearance. Centre values predicted by MNFR-NN and observed values can be seen to be very close to each other in both numerical results and graphical representations.

In the results of the analysis, it was observed that there was a narrowing in the fuzzy prediction interval with the increase in h-level. Narrowing in the fuzzy prediction interval leads to a decrease in model fuzziness. In fuzzy regression analysis, the aim is to provide predictions within the framework of more flexible boundaries compared with the classical regression by digitizing system fuzziness. Narrowing in the fuzzy prediction interval of egg production curves reflects the decrease in fuzziness and increase in credibility of the predicted values. In this context, the appropriate fuzzy prediction interval for EP and EW was obtained on 0.7 h-level. Table 5 shows the AAE values for the MNFR-NN analysis for daily and weekly measured data. As can be seen in Table 5, the upper and lower fuzzy prediction boundaries are very close to each other. This shows that despite the different data set sizes, the method discussed shows consistent results.

Table 6 shows the numerical results of MSE and MAPE values for MNFR-LSSVM. The most successful results obtained in the MNFR-LSSVM analysis were as follows: $\sigma = 50$, $\gamma = 0.4$ for daily data; $\sigma = 90$, $\gamma = 0.7$ for weekly data (Table 6).

Table 7 shows the MNFR-LSSVM analysis AAE values for daily and weekly measured data with RBF kernel function. In Table 7, it is determined that the average distance values of the upper and lower boundaries of the EP and EW fuzzy outputs are quite close to each other. In Figs. 4 and 5, in the results of MNFR-LSSVM analysis, it is seen that the typical appearance of the EP and EW variables is obtained in cases where the level h is 0.7. In addition, the observed values can be seen to be very close to the predicted centre values with MNFR-LSSVM.

When the analysis results are examined comparatively, it can be seen that MNFR-NN achieves the most successful estimation values when compared with other methods.

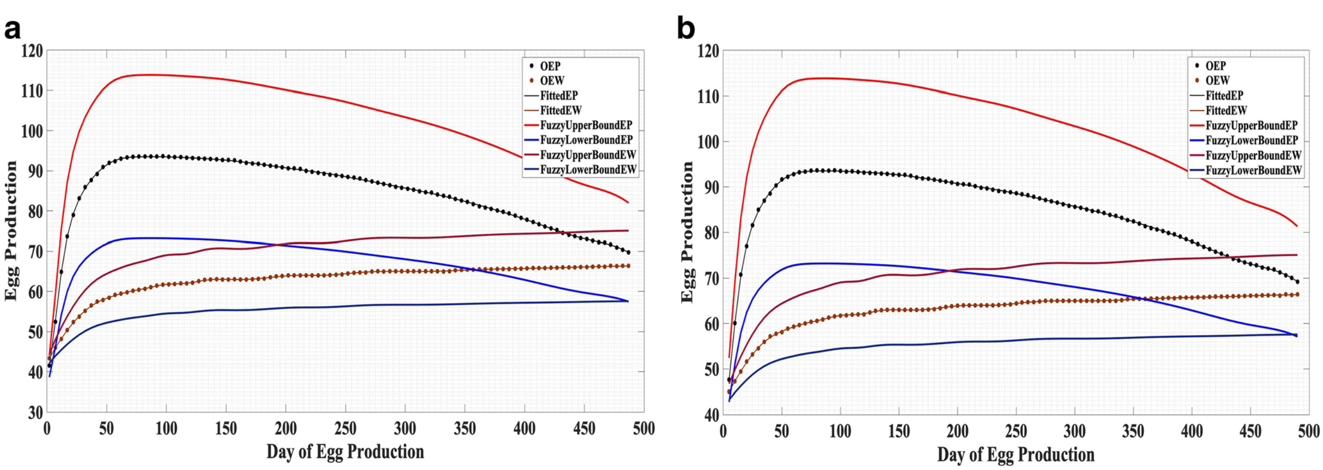

Fig. 2 Results of MNFR-NN for daily measured test (**a**) and validation sets (**b**) ($h = 0.7$)

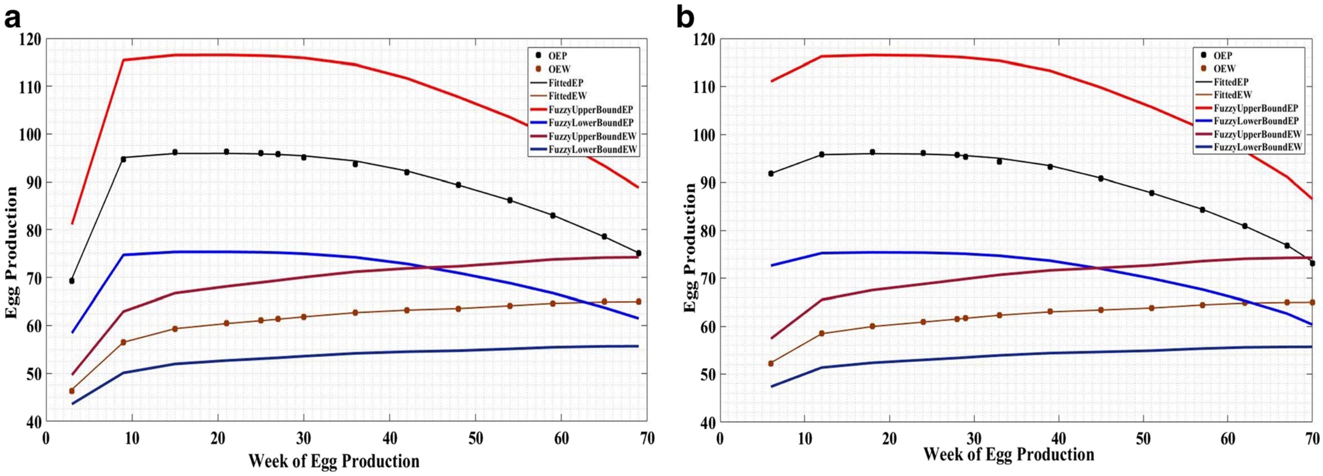

Fig. 3 Results of MNFR-NN for weekly measured test (**a**) and validation sets (**b**) ($h = 0.7$)

When the findings were analysed in terms of daily and weekly time periods, the MNFR method was found to be more consistent in itself, in contrast to classical regression analysis. In the MNFR analysis, the difference in MSE and MAPE values was found to be quite low between daily and weekly data. In the classical regression analysis, the initial values of the parameters and the size of the data set considerably influence the goodness of fit. In neural networks and related methods, the adaptation process is relatively rapid compared with the classical regression due to the automatic adjustment of synaptic weights during the learning process and the parallel placement of data along the layers.

Artificial neural network method can be used as an alternative tool to fit to egg production and growth curve in poultry. Roush et al. (2006), in their study, a comparison was made between the modelling by the Gompertz nonlinear regression equation and neural network modelling with daily live weight data in broiler. In contrast to our study, Roush et al. (2006) determined the number of observations in training and validation sets in equal proportions. Ahmad (2009) aimed to simulate data using published literature for different growth periods and to develop artificial intelligence models with various neural network architectures, in his study. In the study conducted by Ahmad (2009), three different neural networks were used to model the growth curve. Ahmad (2009) showed a different point of view according to other studies in the literature and reported that the backpropagation algorithm is more successful than the others, as in our study. In the studies of modelling of growth curves and neural networks, the processing of the method and the results obtained are consistent with the results obtained in our study (Roush et al. 2006; Yu et al. 2006; Ahmad 2009; Behzadi and Aslaminejad 2010; Kaewtapee et al. 2011). Savegnago et al. (2011) aimed to investigate the possibility of using neural networks on an egg production data set and fitting models to the egg production curve by applying two approaches. Savegnago et al. (2011) have used the measured data for two generations of laying hens in weekly periods. In their study, the odd weeks were used for training and the even weeks were used for testing the neural networks models. In our study, the training set of neural networks was determined as 60% of the whole set of data in both daily and weekly data analyses different from the study performed by Savegnago et al. (2011). Ahmadi and Golian (2008) used data from two generations in order to model egg production curves with neural networks. Unlike our study, the researchers divided the data into two subsets as 80% training and 20% validation sets for each generation, and the results of analysis were presented separately for two generations. Ahmad (2011) performed another study in which the egg curve was modelled by neural networks. Ahmad

Table 5 AAE results for MNFR-NN

Data set	Variable		h-level	AAE^{+}	AAE^{-}	AAE^{c}	AA^{w}
Daily	EP	Test Set	0.7	17.222	17.227	0.0811	114.83
		Validation Set	0.7	17.285	17.286	0.0791	115.24
	EW	Test Set	0.7	7.6218	7.6310	0.0459	50.842
		Validation Set	0.7	7.6739	7.6747	0.0437	51.162
Weekly	EP	Test Set	0.7	18.256	18.076	0.2326	121.1
		Validation Set	0.7	18.539	18.375	0.1776	123.05
	EW	Test Set	0.7	7.9825	7.9577	0.0612	53.134
		Validation Set	0.7	8.2273	8.2618	0.0495	54.964

Table 6 MSE and MAPE Results of MNFR-LSSVM

Data set	Variable	MSE		MAPE	
		Test set	Validation set	Test set	Validation set
Daily[1]	EP	0.016	0.017	0.117	0.085
	EW	0.013	0.004	0.139	0.067
Weekly[2]	EP	0.058	0.113	0.192	0.203
	EW	0.005	0.010	0.103	0.108

[1] $\sigma = 50$, $\gamma = 0.4$

[2] $\sigma = 90$, $\gamma = 0.7$

(2011) aimed to generate random examples from the simulated data for neural network training and testing for the weekly egg production prediction. In his study, three neural network architectures were compared for their efficiency to forecast egg production, along with other traditional models. In our study, 10 different algorithms and two different activation functions were used to analyse in a more detailed perspective in two different time periods, different from mentioned study. Both of results of scientific studies which are using neural networks in order to model egg curves and results of our study are parallel to each other, and it can be seen that the neural networks method is quite successful in curve modelling and can be used as an alternative method to nonlinear regression analysis (Ahmad 2011; Ahmadi and Golian 2008; Ghazanfari et al. 2011; Savegnago et al. 2011). Gorgulu and Akilli (2018) used the LSSVM method to model egg performance in their studies. In our study, LSSVM method was used to construct NFR and successful results were obtained with RBF kernel function, similar to mentioned study. Morales et al. (2016) aimed at developing and testing an early warning model based on support vector machine algorithms, in order to detect problems in egg production curve from commercial hens. Morales et al. (2016) reported that support vector machine method is quite successful in egg production curve analysis, as in our study.

NFR method is used successfully in other applied sciences where the data structures similar to the egg production curve are modelled. Xu and Khoshgoftaar (2001), Xu et al. (2000) and Kahraman and Evren (2012) used the mean and standard deviation of the dependent variable instead of cost function in order to obtain spread values in the nonlinear fuzzy regression analysis process based on the method proposed by Ishibuchi and Tanaka (1992). The mentioned studies reported that NFR models had a substantially higher accuracy of prediction than traditional methods for nonlinear data modelling, as in our study.

He et al. (2016) proposed the use of a random weight network to develop a NFR model. Their experimental results demonstrated that the feasibility and effectiveness of random weight network–based NFR are convergent and it can obtain better regression performance with a simple network architecture, as well as a faster learning speed, compared with existing NFR models based on backpropagation and radial basis function networks. He et al. (2018) proposed a random weight network–based NFR model to solve the trapezoidal fuzzy number–based NFR problem. Their experimental results on fuzzified data sets have demonstrated the superiority of random weight network–based NFR in comparison with the existing NFR model trained with a backpropagation algorithm and the other four NFR models. In both studies conducted by He et al. (2016) and He et al. (2018), similar to our study, it can be seen that increases in h-levels narrow the fuzzy prediction range and nonlinear data structures are very successfully modelled by NFR models.

Data structures in the form of time series, similar to the egg production curves, are successfully modelled with NFR-LSSVM. Lin and Pai (2010) used a fuzzy support vector regression model to forecast an index of business cycle and to calculate fuzzy lower and upper limits, then make predictions by fuzzy h-level set. As in the present study, Lin and Pai (2010) have examined different h-levels and the best performance was obtained with h=0.3. Lin et al. (2013) developed a fuzzy least-squares support vector regression model with genetic algorithms (FLSSVRGA) to forecast seasonal revenues. Lin et al. (2013) used the h-level to control the possibility distribution range yielded by the fuzzy model and to provide the fuzzy prediction interval in their method. Similar to our study, three different kernel functions were used to obtain the fuzzy prediction range. The present study results confirm that

Table 7 AAE results for MNFR-LSSVM

Data set	Variable		h-level	AAE^+	AAE^-	AAE^c	AA^w
Daily	EP	Test set	0.7	17.218	17.230	0.0940	114.82
		Validation set	0.7	17.287	17.286	0.0982	115.24
	EW	Test set	0.7	7.6220	7.6308	0.0886	50.843
		Validation set	0.7	7.6727	7.6752	0.0881	51.160
Weekly	EP	Test set	0.7	18.131	18.188	0.1567	121.06
		Validation set	0.7	18.484	18.396	0.2166	122.93
	EW	Test set	0.7	7.9766	7.9603	0.0598	53.123
		Validation set	0.7	8.2092	8.2682	0.0659	54.924

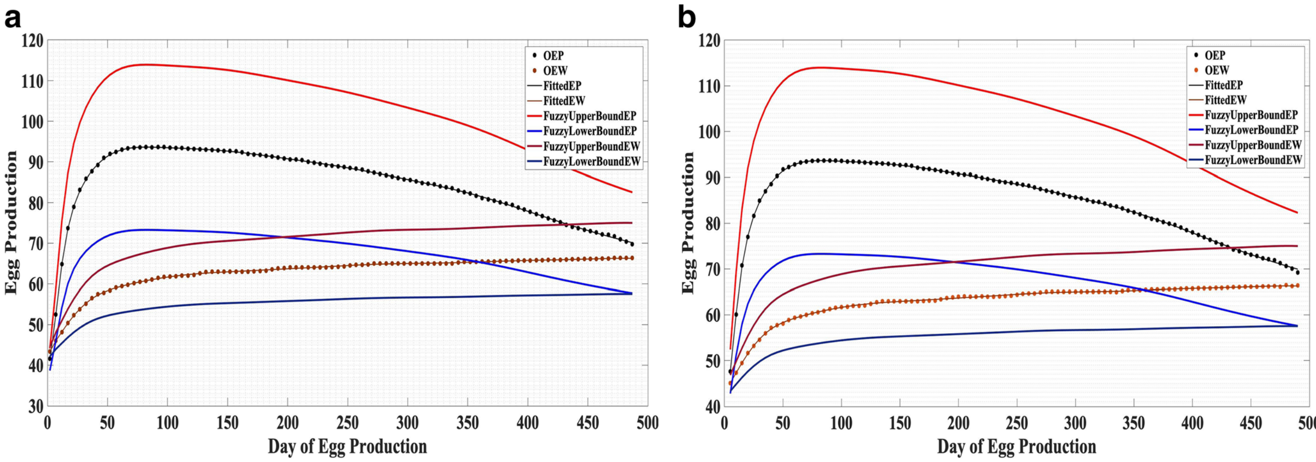

Fig. 4 Results of MNFR-LSSVM for daily measured test (**a**) and validation sets (**b**) ($h = 0.7$)

the NFR method is a very powerful tool in nonlinear and time series modelling.

Conclusions

In this study, it is aimed to investigate the egg production data by MNFR analysis and to compare the research findings with classical regression analysis. The analysis results show that the MNFR method is much more successful and can be used alternatively in both daily and weekly measured data compared with the multivariate classical nonlinear regression.

Lots of existing models of both EP and EW do not properly present uncertainty. The most important contribution of this study to poultry science is NFR models for fuzzy prediction interval provide a systematic framework for representation of uncertainty. In the egg production process, MNFR analysis was performed with NN and LSSVM in order to express the uncertainty in the system structure, and fuzzy prediction ranges were obtained for both dependent variables. Fuzzy prediction ranges provide a more flexible interpretation of egg curves, which are of critical importance in poultry nutrition and breeding, compared with conventional methods. In commercial layers, the probability distribution of yield values on individual or poultry basis is determined so that the possible forecast range is obtained. The forecast range provided by MNFR reveals the production potential of laying hens in a fuzzy context. In this process, MNFR analysis provides a flexible perspective to researchers. One of the basic elements of this perspective is that classical regression analysis assumptions do not have to be provided in MNFR analysis. Another factor is that the numerical results of the environmental impacts affecting the system output can be included in the model. In other words, the number of input variables in the model may be more than one.

Egg performance predictions and production plans based on estimation values are of great importance for poultry breeding. The properly modelling of the production pattern and the selection of the most successful prediction methods play an important role in the design of the change in feeding and

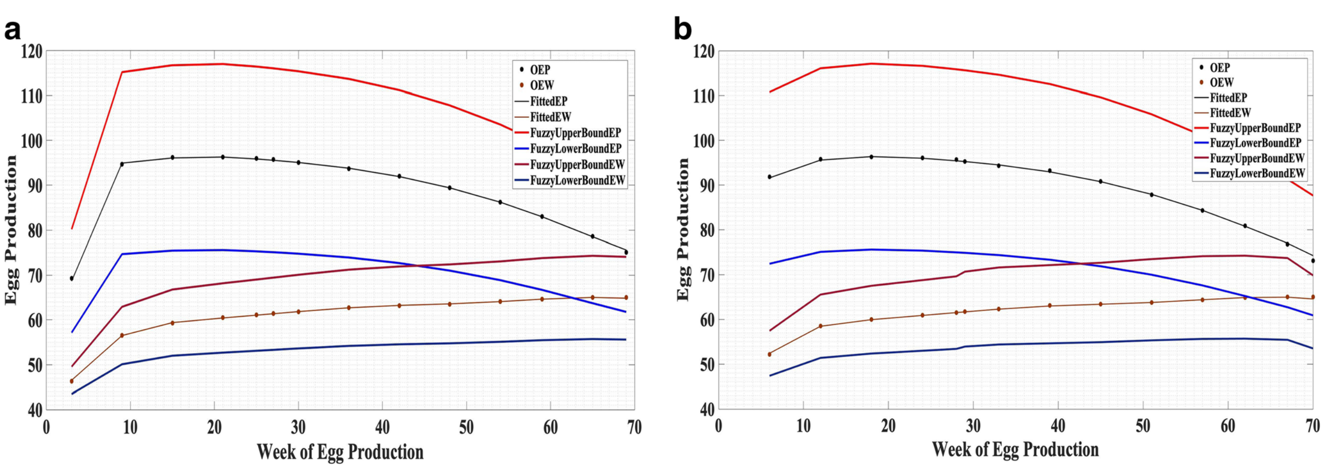

Fig. 5 Results of MNFR-LSSVM for weekly measured test (**a**) and validation sets (**b**) ($h = 0.7$)

nutrition applications over time and in the design of forward-looking management plans for poultry producers.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interests.

Ethical standards The manuscript does not contain clinical studies or patient data.

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