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Egg production curve fitting using least square support vector machines and nonlinear regression analysis

Kurvenanpassung der Legeleistung mit Hilfe von Kleinste Quadrate Support Vektor Maschinen und nichtlinearer Regressionsanalyse

O. Görgülü[1*] and **A. Akilli**[2]

[1] Department of Biostatistics and Medical Informatics, Faculty of Medicine, Ahi Evran University, Kirsehir, Turkey

[2] Department of Biometry and Genetic, Faculty of Agriculture, Ahi Evran University, Kirsehir, Turkey

*Correspondence: ozkangorgulu@gmail.com

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Abstract

It was aimed to model egg production curves using nonlinear regression analysis and least squares support vector machines in this study. The accuracy of the models was calculated using the Akaike information criteria, mean square error, mean absolute percentage error, mean absolute deviation, R^2 and AdjR^2. The data set consisted of egg performance values of laying hens recorded from 20 weeks to 70 weeks of age. The longitudinal data had a nonlinear structure. The results showed that the least squares support vector machines method, which is considered in different parameter combinations, can be used as an alternative to classical methods and predictions have lower errors. The present study shows that least squares support vector machine methods can be used successfully in the modelling of egg production curves in laying hens.

Key words

egg production, last square support vector machine, curve fitting, regression, poultry

Zusammenfassung

Kurvenanpassung der Legeleistung mit Hilfe von Kleinste Quadrate Support Vektor Maschinen und nichtlinearer Regressionsanalyse

Ziel dieser Studie war, Legeleistungskurven mit Hilfe von nichtlinearer Regressionsanalyse und Kleinste Quadrate Support Vektor Maschinen zu modellieren. Die Genauigkeit der Modelle wurde mit Hilfe des Akaike-Informationskriteriums, des mittleren quadratischen Fehlers, des mittleren absoluten prozentualen Fehlers, der mittleren absoluten Abweichung, R^2 und AdjR^2 berechnet. Der Datensatz besteht aus Legeleistungswerten von Legehennen, die für das Alter von 20 Wochen bis 70 Wochen aufgezeichnet wurden. Die Daten ändern sich mit der Zeit und weisen eine nichtlineare Struktur auf. Die Analyseergebnisse zeigen, dass die Kleinste Quadrate Support Vektor Maschinen Methode, die in verschiedenen Parameterkombinationen betrachtet wurde, als Alternative zu klassischen Methoden verwendet werden kann und Vorhersagen mit geringeren Fehlern liefert. Die Studie ergab, dass die Kleinste Quadrate Support Vektor Maschinen Methode eine neue Methode ist, die bei der Modellierung von Legeleistungskurven für Legehenne verwendet werden kann.

Stichworte

Legeleistung, Kleinste Quadrate Support Vektor Maschine, Kurvenanpassung, Regression, Geflügel

Introduction

In various applications in poultry breeding and feeding, the dependent variable can vary with time. Time-varying data can be represented by non-linear functions and usually have a curvilinear structure. In models developed under nonlinear regression analysis, curvilinear relations and iterative methods are used to predict parameters. Various models that can adopted to cater for different data structures.

Egg production can be modelled by nonlinear regression analysis in poultry. The purpose of using egg production curves is to determine the effects of various applications on poultry production output and its change over time. The egg production curve describes the laying pattern of a hen population over time and it can be used to investigate production percentage or number of eggs as affected by layer age (NARUSHIN and TAKMA, 2003; SAVEGNAGO et al., 2012). In addition to these parameters another description related to egg production is egg yield. It is defined as the number of eggs from a poultry house (hen-housed) or the total number of eggs produced in relation to live hens (hen-day) during a specific time period (daily, weekly, monthly, annually) or as the ratio of total number of eggs produced to the number of animals (NARINC et al., 2014). The egg production curve is necessary to make economic projections for laying hens (ADAMS and BELL, 1980). It can also be monitored in order to detect problems in the production indicating a possible disease or other issues (MORALES et al., 2016). An increasing production can be seen to the peak of the curve and a steady decline thereafter to the end of the subsequent production process. Similar to the lactation curves of dairy cattle and growth curves, different models of the egg yield curves can be used. These models were derived to represent the individual or herd-based production cycle of chickens (MCMILLAN, 1981, GAVORA et al., 1982; FIALHO and LEDUR, 1997; GROSSMAN et al., 2000; NARUSHIN and TAKMA, 2003).

In recent years, along with technological improvements, limitations on the calculation possibilities in nonlinear functions have gradually decreased. In this context, alternative artificial intelligence-based methods for regression analysis have emerged and are widely used in the field of life sciences. These methods are subject to many successful applications. They are mainly functions such as prediction, classification and clustering and can be used as an alternative to nonlinear regression analysis. Publications in which artificial neural networks are used for egg performance modelling are abundant (AHMADI and GOLIAN, 2008; AHMAD, 2011; SAVEGNAGO et al., 2011; SEMSARIAN et al., 2013; ALIQIARLOO et al., 2017).

The work on support vector machines (SVM) is based on the research done in 1960 by Vladimir Vapnik and Alexey Chervonenkis on statistical learning theory. The first article about this subject was published in 1992 by Vladimir Vapnik, Bernhard Boser and Isabelle Guyon (BOSER et al., 1992; HAYKIN, 1999; SUYKENS et al., 2002; HAN et al., 2006). SVM uses Kernel-based methods. In non-linear regression using Kernel-based methods, modelling power is quite high. Least square support vector machine (LSSVM) is a very successful approach in modelling nonlinear function structures. This method is used especially for the solution of regression problems. LSSVM is also defined as a special kind of the Kernel-based models (HAYKIN, 1999, SUYKENS et al., 2002). Also, it is defined as another artificial intelligence method that performs machine learning and has a work structure similar to artificial neural networks. In the literature, nonlinear regression analysis was used in poultry (ZHU and MA, 2011; HE et al., 2014; MORALES et al., 2016; WARANUSAST et al., 2016), and applied sciences (BORIN et al., 2006; WU et al., 2008; WU et al., 2010; BALABIN and LOMAKINA, 2011; SONG et al., 2011; EKICI, 2014; ESTEKI et al., 2017). In a literature review, support vector machines were found to be used only in one study to provide early detection of problems encountered in the egg production process (MORALES et al., 2016). However, there was no study of LSSVM in the modelling of egg curves. This study aimed to be the first study in poultry.

In this study, nonlinear regression analysis and LSSVM were examined comparatively for investigation of egg production performance in laying hens. Adams-Bell, Compartmental, McNally, and Logistic models were used in the nonlinear regression analysis for this purpose. Radial basis function (RBF) and Polynomial Kernel (Poly Kernel) functions were used to examine a numerical example for LSSVM analysis.

Material and Methods

Two data sets from two generations of laying hens were used. The first data set contained the % hen day egg yield for a 50-week period, starting at week 19 of age and finishing at week 70 of age. The second set of data related to the next generation and contained the mean weekly % egg yield over the same period. The daily egg production rate was measured as percentage. The first data set was divided into two subsets for the training and testing phases of LSSVM and nonlinear regression models. The data set was randomly divided into two groups by 80% training and 20% test data sets. The training data set summed up 280 days and the test data set summed up 70 days. The second set of data was used to validate both LSSVM and nonlinear regression model, as well as to ascertain whether these models could be used on other data sets that did not participate in the construction of these models. The accuracy of the models was measured at each phase. The fitting, testing and validation of the nonlinear regression models and the training, testing and validation of LSSVM were done using MATLAB R2016a.

Egg production curves

The egg production process can be modelled by non-linear regression analysis (Table 1) to represent the individual or herd-based production cycle in layers. The egg production curve is an indication of the average production rate of laying hens. Parameters were estimated by Levenberg–Marquardt iteration algorithm using MATLAB (R2016a). A convergence criterion was $1.0\text{x}10^{-8}$. All initial values of the parameters were taken from previous studies and trial and error method.

Table 1. Nonlinear functions

Nichtlineare Funktionen

Nonlinear Functions	Equations	Description
Adams-Bell Model	$y_t = \frac{1}{0.01+ar^{(t-b)}} - c(t-d)$	a, b, c, d and r are constants
Compartmental Model McMillan (1981)	$y_t = a(e^{-ct} - e^{-bt})$	c = daily rate of increase in egg production; d = mean initial day of egg-laying; x = rate of production decrease after the peak.
McNally Model McNally (1971)	$y_t = at^b e^{(-ct+dt^{0.5})}$	b, c, and d are constants
Logistic Model Nelder (1961)	$y_t = a\{1+e^{(b-(ct))}\}^{-1} e^{-xt}$	c = reciprocal indicator of the variation in day of production of first egg; d = mean day of egg production at sexual maturity; x = rate of production decrease after the peak.

y_t = egg production rate at t days of laying; a = asymptotic value of egg production at the peak of egg-laying.

Least Square Support Vector Machines (LSSVM)

Support vector machines (SVM) are a very popular approach based on statistical learning theory and performing supervised learning. SVM is used to solve nonlinear classification and multivariate function estimation or nonlinear regression problems (Vapnik, 1998, Suykens, 2001; Smola and Schölkopf, 2004). This method uses non-linear Kernels and has high generalization ability. on the other hand, LSSVM has been proposed as a special type of SVM in order to reduce the complexity of the optimisation processes in quadratic programming problems. At this point, the aim is to substitute equality constraints for equality in order to obtain a linear equation set instead of a quadratic programming problem in the dual space. (Suykens and Vandewalle, 1999). LSSVM uses the least squares cost function to solve the determined optimisation problem. LSSVM differs from SVM in this respect (Suykens et al., 2002; Suykens, 2003; Li et al., 2012). The function definition for the LSSVM regression is Equation 5; estimation problem Equation 6; the constraint is defined in Equation 7:

$$y(x) = w^T \varphi(x) + b \quad [5]$$

$$\min_{w,b,e} J(w,e) = \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{i=R}^{N} e_i^2 \quad [6]$$

$$y_i = w^T \varphi(x_i) + b + e_i \; i = R, \ldots, N \quad [7]$$

In the equations above, the training set $\{x_i, y_i\}$ is the model parameters $w \in \mathbb{R}$ and $b \in \mathbb{R}$. Equation 5 w; weight vector, and b is the deviation term. φ nonlinear mapping function $\varphi: \mathbb{R} \rightarrow \mathbb{R}$. The regression model in Equation 5 is constructed using the nonlinear mapping function. As in SVM theory, LSSVM also minimises the cost function (J) with penalised regression error. The cost function is given in Equation 6. The weights are arranged in the first part of the cost function. The second part is the regression error for all training data. The parameter γ is determined by the user (Borin et al., 2006; Bessedik and Hadi, 2013).

Feature space is usually high dimensional. In Kernel-based techniques, φ is not explicitly defined, but a certain positive term called K is specified via the Kernel Function. Based on the Mercer conditions (Mercer, 1909), each positive definite $K(x_i,x_j)$ function is expressed as the inner product of $K(x_i,x_j)=\varphi(x_i)^T\varphi(x_j)$. If feature space is multidimensional, Lagrange dual formulation is used to design more practical solutions. The Kernel matrix is defined as $\Omega_{ij}=\varphi(x_i)^T\varphi(x_j)=K(x_i,x_j)$, $(i,j=1,\ldots,N)$. With the application of Mercer conditions to the matrix Ω, LSSVM for regression is obtained by the expression in Equation 8 (Suykens and Vandewalle, 2000; Suykens et al., 2002; Zhu and Wei, 2013).

$$y(x)=\sum_{i=R}^{N}\alpha_i K(x,x_i)+b \quad [8]$$

Kernel implementations were used with the MATLAB training and simulation procedure. Analyses were performed using two different Kernel functions in the training process of the data. These were the Radial Basis Function (RBF) and the Polynomial Kernel Function. Analyses were performed on different parameter combinations to determine the optimal values of the model parameters. The parameter σ was in the range of 10–90; γ was considered in the range of 0.1–0.9. The most successful estimates were obtained when the RBF Kernel function was σ = 90 and γ = 0.1. The most successful estimates were provided if the function level was five for Polynomial Kernel function. Kernel functions are described in Table 2.

Table 2. Kernel Functions

Kernel-Funktionen

Kernel Functions	Equations	Description
Radial Basis Function (RBF)	$K(x_i,x_j)=e^{-\frac{\lVert x_i-x_j\rVert^2}{\sigma^2}}$	σ^2 is the variance of the Gaussian Kernel.
Polynomial Kernel Function	$K(x_i,x_j)=(x_i^T x_j+t)^d, t\geq 0$	*t* is the intercept and d the degree of the polynomial.

The accuracy of the models was calculated using the Akaike Information Criteria (AIC), Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), R^2 and AdjR^2. The R^2 is an indicator of how well the model fits the data. The AIC, MSE, MAPE and MAD are described in Table 3.

Table 3. Statistical error criteria for evaluating the curve fitting

Statistische Fehlerkriterien zur Beurteilung der Kurvenanpassung

Statistical Error Criteria	Equations
Akaike Information Criteria (AIC)	$AIC = n.ln\left(\frac{SS_{error}}{n}\right) + 2.k$
Root Mean Square Error (MSE)	$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
Mean Absolute Percentage Error (MAPE)	$MAPE = (\frac{100}{n})\sum_{i=1}^{n}\left\|\frac{(y_i - \hat{y}_i)}{y_i}\right\|$
Mean Absolute Deviation (MAD)	$MAD = \frac{\sum_{t=1}^{n}\|y_t - \hat{y}_t\|}{n}$
Adj. Coefficient of Determination (AdjR^2)	$AdjR^2 = 1 - (1 - R^2)\frac{(n-1)}{(n-p-1)}$

Where for the ith record, $\hat{y}_i$: predicted value, y_i: actual value, n: number of records.

Results

In the non-linear regression analysis, Figure 1 represents the first production period defined as the test set. The second production period defined as the set of validation is represented by the graphs in Figure 2. The results of the analysis of the test and validation sets are given in the graphs as follows, respectively; Figure 1 (a) – Figure 2 (a) Adams-Bell model, Figure 1 (b) – Figure 2 (b) Compartmental model, Figure 1 (c) – Figure 2 (c) Logistic model, Figure 1 (d) – Figure 2 (d) is the McNally model. In the analyses, it was determined that all models fit well with the data sets. Graphical analyses show that the Adams Bell model catches the highest value of the egg production curve best. Table 4 and Table 5 show the error statistics calculated for the predicted values of the egg performance curve fit for the test and validation set. Accordingly, it was determined that for both the test and validation data sets, the Adams Bell model performed with lower error than the others and had the best matching model. In equations 12 and 13, the Adams Bell model has the model structure obtained for the test and validation set, respectively.

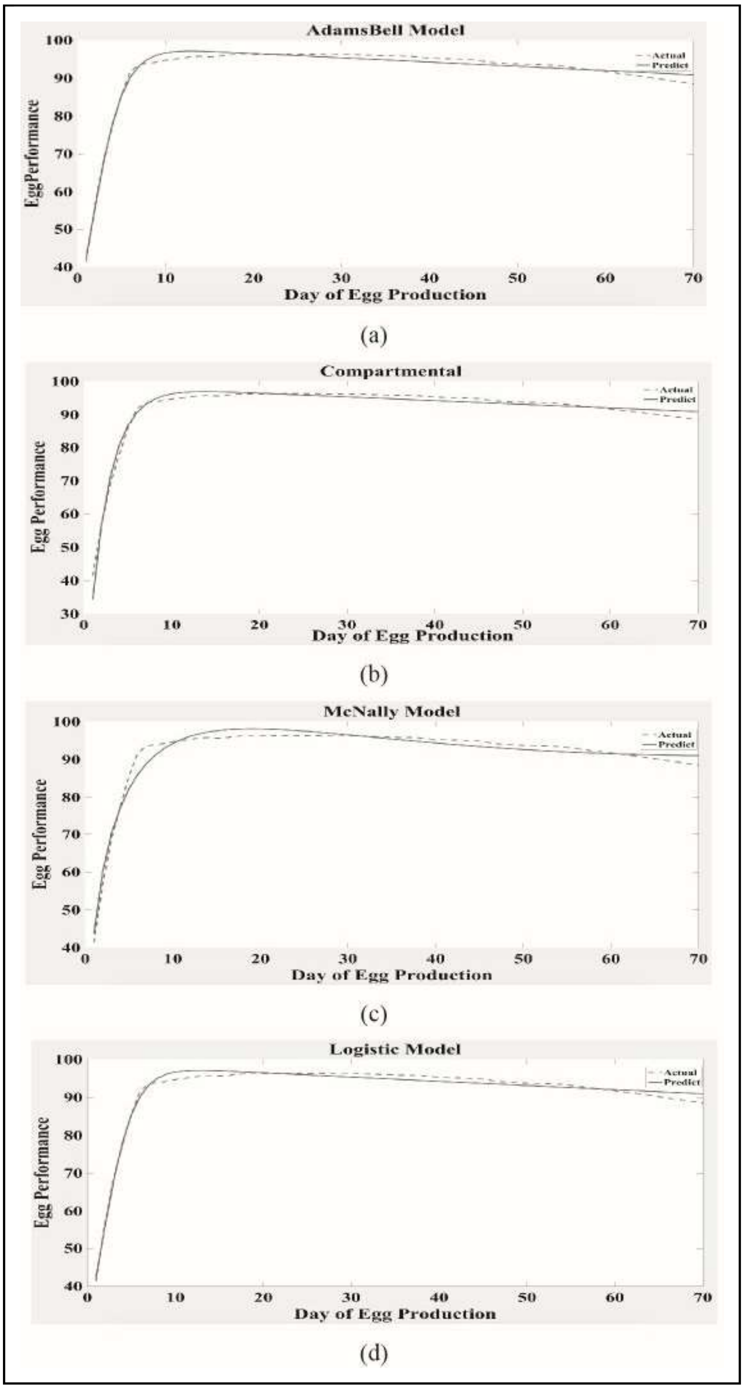

Figure 1. Fitted curves for daily egg performance using Adams Bell (a), Compartmental (b), McNally (c) and Logistic models for laying hens in the test phase.

Kurvenanpassung für die Tageslegeleistung der Legehennen in der Testphase mittels Adams Bell- (a), Kompartiment- (b), McNally- (c) und logistischer Modelle

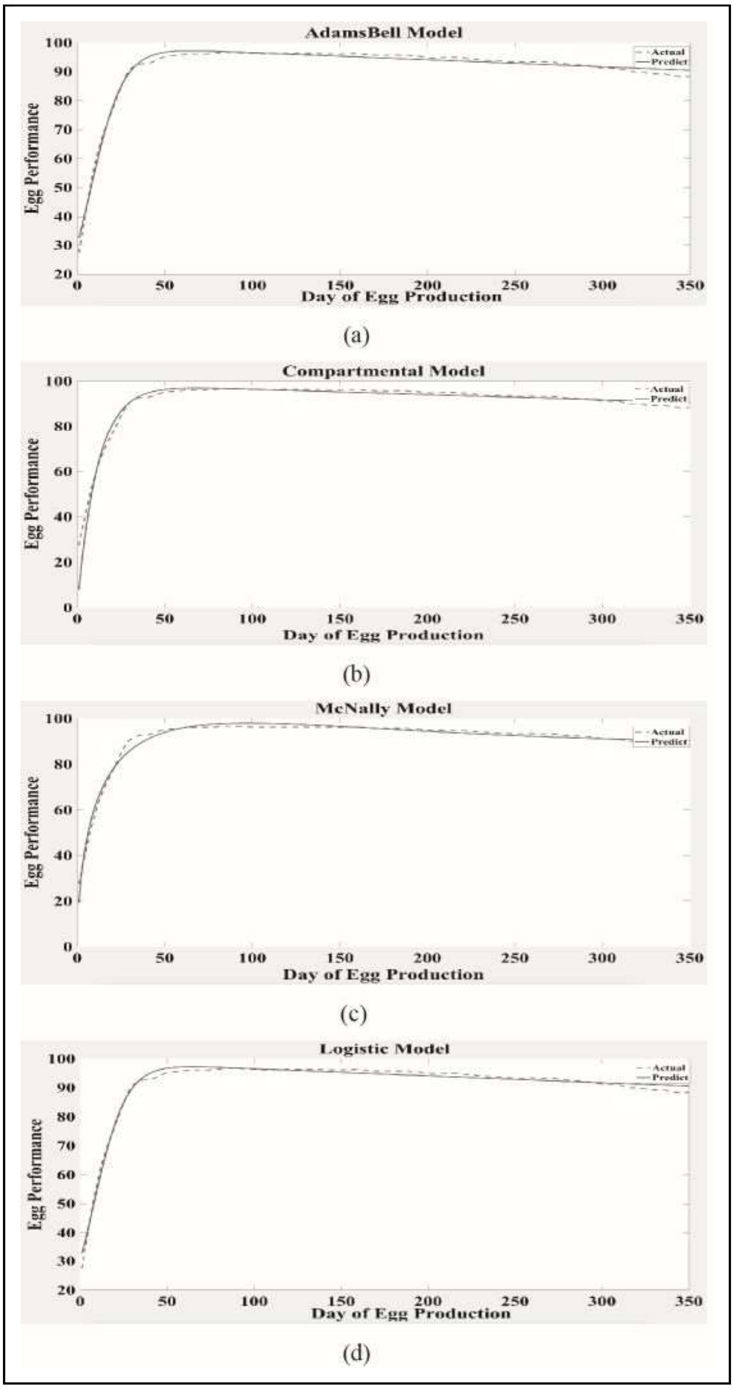

Figure 2. Fitted curves for daily egg performance using Adams Bell (a), Compartmental (b), McNally (c) and Logistic models for laying hens in the validation phase.

Kurvenanpassung für die Tageslegeleistung der Legehennen in der Validierungsphase mittels Adams Bell- (a), Kompartiment- (b), McNally- (c) und logistischer Modelle

Table 4. Statistical criteria for evaluating the curve fitting of the nonlinear regression models for test and validation data sets

Statistische Kriterien zur Beurteilung der Kurvenanpassung von nichtlinearen Regressionsmodellen für Test- und Validierungsdatensätze

Datasets	Models	AIC	MSE	MAPE	MAD	R^2	$AdjR^2$
Test dataset	Adams Bell	16.641	1.09	1.00	0.90	0.985	0.984
	Compartmental	52.062	1.93	1.25	1.02	0.974	0.973
	McNally	75.598	2.62	1.46	1.29	0.965	0.964
	Logistic	17.087	1.13	1.01	0.91	0.985	0.984
Validation dataset	Adams Bell	72.171	1.19	1.08	0.90	0.988	0.987
	Compartmental	501.16	4.11	1.65	1.12	0.958	0.957
	McNally	276.69	2.15	1.38	1.12	0.978	0.977
	Logistic	85.276	1.24	1.10	0.91	0.987	0.986

Table 5. Statistical criteria for evaluating the curve fitting of LSSVM with Kernel Functions for test and validation data sets

Statistische Kriterien zur Beurteilung der Kurvenanpassung von LSSVM und Kernel-Funktionen für Test- und Validierungsdatensätze

Kernel Functions	Datasets	AIC	MSE	MAPE	MAD	R^2	$AdjR^2$
RBF Kernel[1]	Test-set	−162.069	0.093	0.204	0.162	0.9994	0.9993
	Validation-set	−71.457	0.806	0.680	0.469	0.9983	0.9982
Polynomial Kernel[2]	Test-set	135.395	6.534	2.299	1.958	0.9557	0.9543
	Validation-set	650.261	6.710	2.412	1.838	0.9673	0.9671

[1] $\sigma = 90$ ve $\gamma = 0.1$; [2] d = 5

$$y_t = \frac{1}{0.01+0.331*0.582^{(t-(-5.008))}} - 0.112(t-(-11.292)) \quad [12]$$

$$y_t = \frac{1}{0.01+0.157*0.9^{(t-(-18.578))}} - 0.024(t-(-41.761)) \quad [13]$$

Statistical error criterion values calculated using predictive values and actual values of the LSSVM method working with RBF and Polynomial Kernel function are given in Table 4 for the test and validation set, respectively. In the analyses performed with the RBF Kernel function, σ and γ parameters are handled in different combinations. The most successful estimates for the first and second egg production period were obtained when σ = 90 and γ = 0.1. In the Polynomial Kernel analysis, the function degree is considered between one and five. In the modelling of the egg production curve, the most successful predictions were obtained with a function degree of five.

Figures 3 (a) and 3 (b) show the observed % hen day egg yield and LSSVM predictions with RBF Kernel functions for the test and validation sets, respectively. The first period of daily egg production was used for the test phase and the second production period was used for the model validation. In graphs, it seems that curve fits for both test and validation sets are quite good.

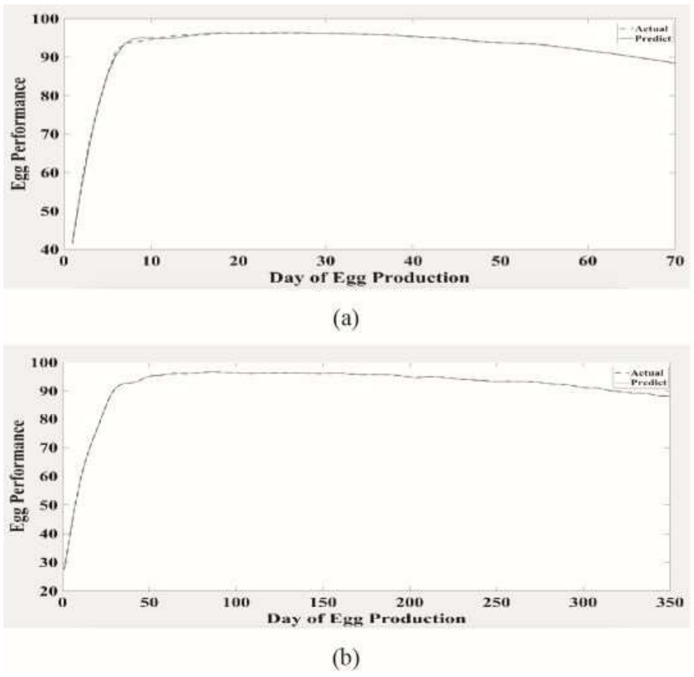

Figure 3. Fitted curves for daily egg performance using LSSVM with RBF Kernel Function for laying hens in the test (a) and validation (b) phases.

Kurvenanpassung für die Tageslegeleistung der Legehennen in der Test-(a) und Validierungs(b)-Phase mittels LSSVM und RBF Kernel-Funktion

Figures 4 (a) and 4 (b) show representations of the actual values and LSSVM predictions with Poly Kernel functions of the test and validation set, respectively. It was determined that the curves representing the predicted values were fluctuating and therefore the egg performance curve moved away from the typical view. Among the Kernel functions studied in scope of the study, RBF Kernel is the function that best catches the nonlinear structure of egg performance curves and performs the most successful predictions.

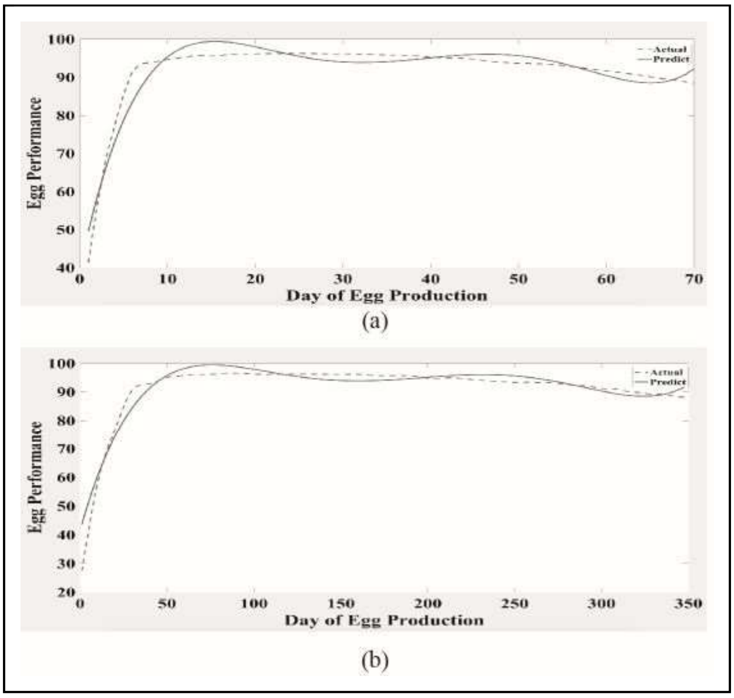

Figure 4. Fitted curves for daily egg performance using LSSVM with Poly Kernel Function for laying hens in the test (a) and validation (b) phases.

Kurvenanpassung für die Tageslegeleistung der Legehennen in der Test-(a) und Validierungs(b)-Phase mittels LSSVM und polynomialer Kernel-Funktion

When comparing two different Kernel functions evaluated in the LSSVM method with the Adams Bell model, the most successful estimates for both the test and validation sets were obtained by the LSSVM method working with the RBF Kernel function. The results of the analysis show that the LSSVM method can be used as an alternative tool for egg production curve fitting. In nonlinear regression analysis, the curve fitting is significantly affected by the initial values of the parameters included in the models and the size of the data set. on the contrary, the curve fitting process is quite fast in the LSSVM method.

Discussion

Savegnago et al. (2012) performed nonlinear regression models and segmented polynomial models on selected and unselected chicken lines using weekly egg production rates. For this purpose, Logistic, Compartmental I, McNally, Compartmental II, Yang, Segmented Polynomial and Persistency models were discussed. The data consisted of egg production rate records for 17–70 week old layers. Logistic, Yang, Segmented Polynomial models had the best fit. In the present study, the curve fitting was taken for two different production periods in a longer period of time. Froom the error criteria and graphical representations of the models used in the present study it shows that they are compatible with published studies.

Artificial neural network is a widely used artificial intelligence method that performs supervised learning similar to the LSSVM method and is widely used in livestock. There are artificial neural network studies subject to alternative and curve fitting to nonlinear regression analysis on animal breeding in the literature. (Roush et al., 2006; Yu et al., 2006; Ahmad, 2009; Behzadi and Aslaminejad, 2010; Kaewtapee et al., 2011). For most of the studies on egg yield curves, neural network training processes are similar to growth curves. In Savegnago et al. (2011), they used weekly measurements of laying hens for two generations. The odd-numbered weeks are used to train the neural network and the even-numbered weeks are used for testing. The second-generation data set was included in the analyses to examine the validity of the models. In the present study, determining the training, testing and validity sets of the LSSVM is similar to the study conducted by Savegnago et al. (2011). Ahmadi and Golian (2008) used two generations of data obtained by modelling egg production curves with neural networks and the results of analysis were presented separately for two generations, in a similar way to the present study. Unlike the present study, the data for each generation were divided into two parts: 80% education and 20% validation. Ahmad (2011) conducted another study of egg production with neural networks. Similar to the work done by AHMAD (2009), a data set of real data was used to simulate Monte Carlo procedures. The method was used to estimate and evaluate the performance of neural networks that they had never seen. Literature shows that neural networks can be a method alternative to nonlinear regression analysis and very successful prediction values are obtained. In addition, the results of these studies are in accordance with the results obtained in the present study (AHMADI and GOLIAN, 2008; AHMAD, 2011; GHAZANFARI et al., 2011; SAVEGNAGO et al., 2011).

MORALES et al. (2016) aimed to develop and test an early warning model based on SVM algorithms for problem determination in egg production. Similar to the present study, the RBF Kernel function compared results for different parameters. The results of the present study are consistent with the study by MORALES et al. (2016). These researchers suggested that the proposed model may be used to reduce economic losses due to delayed treatment and may have positive effects on the productivity. The power of LSSVM for modelling linear and nonlinear regression problems is quite high. At the same time, as in the present work, various studies were done on time series. ZHANG et al. (2013) used the LSSVM algorithm to forecast the future stream flow discharge using the past stream flow data and gage height, which is related to regularisation networks and Gaussian processes. Similar to the present study, the RBF Kernel function is handled in different parameter combinations. TAN et al. (2012) has applied LSSVM algorithms to construct non-linear time series forecasting models to predict river water quality. The results were compared with two different neural network models and it was stated that the LSSVM method made more accurate estimations. SAMSUDIN et al. (2011) proposed a novel hybrid-forecasting model, which combines the group method of data handling (GMDH) and LSSVM. The results were compared for different model constructions. The results indicated that the best performance could be obtained by GLSSVM models. The results of the present study are in accordance with the results of the mentioned studies. The LSSVM method was very successful, especially in the analysis of time series data in the field of life sciences. In the present study, Kernel functions are dealt with in much more detail than in other studies and the results are compared with those obtained with classical methods. From this it follows that LSSVM is a method that can be improved for egg production curve fitting and prediction studies and is promising for future studies.

Conclusion

1. This study is one of the first to use LSSVM for predicting the egg production curve in layers.
2. The results of the study show that RBF Kernel function used in the LSSVM model is more successful than nonlinear regression models. Furthermore, the results of the analysis show that LSSVM successfully captures the nonlinearity of egg production curves.
3. The most important advantage of LSSVM is that there is no need to satisfy assumptions, which is a necessity in regression analysis. At this point, the LSSVM has a more flexible structure. Studies on curve fitting for egg production provide great support to decision-makers and researchers in animal breeding and herd management.
4. The data of the study were obtained by controlling the environmental conditions affecting the egg production process. The results of the study are only interpreted for the data set covered in the study. Another important advantage of the LSSVM method is that, in the case of environmental influences, more than one input information can be included in the model.

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