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ESTIMATION OF 305-DAYS MILK YIELD USING FUZZY LINEAR REGRESSION IN JERSEY DAIRY CATTLE

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ABSTRACT

Fuzzy linear regression analysis helps to produce successful assumptions in situations with uncertainty between variables and provides researchers with a flexible perspective. In this study, 305 days milk yield estimation studies were carried out using partial lactation records of Jersey cattle with the fuzzy linear regression method. Calving age, number of lactation, days of milk, calving season, and the first four milk test days records were used as the independent variables in the study. Also,305 days milk yield was used as the dependent variable. Reliability of the obtained estimates was discussed using graphical representations of *h* values and three different statistical error criteria (RMSE, MAPE and R). In addition, the estimated values obtained were compared with the observed values. The fuzzy linear regression equations developed for 10 different *h* values shows that the equations obtained for the $h = 0.4$ and $h = 0.5$ values are the closest observed values to305 days milk yield. The difference between the predicted values and the observed values was statistically insignificant ($p>0.05$). These results show that the fuzzy linear regression method can be successfully used to predict 305 days milk yield at the beginning of the lactation.

Keyword: Fuzzy regression, Fuzzy linear programming, Dairy cattle, Milk yield.

INTRODUCTION

In dairy cattle, milk yield, one of the most important quantitative traits, is limited by a common effect of genotype and environmental factors (Topal *et al*., 2010). This quantitative trait, which has considerable variation, may be progressed by applying for effective selection program along with providing appropriate environmental conditions. In order to conduct selection programs and to estimate genetic parameters on milk yield, pedigree records of all cows should be available. In addition, the effects of environmental factors, such as calving year, calving interval, calving season, parity, herd and milking frequency on milk yield should also be investigated to perform selection programs (Javed *et al*., 2007; Eyduran *et al*., 2013). The dairy cattle selection at an early age on the basis of part yields considered useful for the dairy farmer as it reduces the cost of raising the animals and also helps for progeny testing. In dairy cattle, a high rate of genetic improvement is only possible through early culling of low producing cows. This can be achieved by selecting cows and bulls on the basis of their part records provided. So, full lactation yield can be accurately predicted from the part yields. Predicting total lactation yield on the basis of part lactation records has a practical utility (Ranjan *et al*., 2005).

Different modelling methods, such as multiple regression, mixed model least squares and maximum likelihood, artificial neural network, nonlinear auto regressive model and regression tree method based on CHAID, and Exhaustive CHAID data mining algorithms were used to estimate 305 days lactation yield from test-day milk yield records in dairy cattle (Grzesiak *et al*., 2003; Pereira *et al*., 2004; Ranjan *et al*., 2005; Sharma *et al*., 2007; Gorgulu, 2012; Eyduran *et al*., 2013). In recent years, it is observed that the literature yields a gradual increase of alternative methods to the regression analysis in performing functions such as assumptions, categorization, etc. One of these methods is the fuzzy regression analysis, which emerged as an alternative to the ordinary regression analysis as a result of the application of the fuzzy logic in the regression analysis. The fuzzy regression analysis is a powerful method used as an alternative to the ordinary regression analysis in situations where the relation between the dependent and independent variables are vague, the definition of the model is insufficient or the assumptions to administer the ordinary regression analysis are not met. Furthermore, fuzzy regression analysis is preferred in situations where exact numerical data are not obtained; in other words, where the verbal statements and humanistic judgments are defined as fuzzy numbers (D'urso and Gastaldi, 2000; Panik, 2009).

The fuzzy regression analysis in research areas with real life material and animal husbandry is relatively new method. The literature yielded no study related to the use of fuzzy linear regression analysis in the predictions of the 305-days milk yield. In this study, the aim is to obtain the predicted value of 305-days milk yield in dairy cattle through the use of fuzzy linear regression model. For this aim, information on fuzzy linear regression analysis was presented, and the parameter prediction method, which is grounded on the approach of fuzzy linear programming, was comparatively investigated. This study will be a theoretical and applied resource for researchers who work in this research field. In the forthcoming studies different fuzzy linear regression techniques and artificial intelligence integrated methods are intended to be used for prediction.

MATERIALS AND METHODS

The data of the study consists of information of the milk yield on the test day of Jersey dairy cattle, calving age (X_1), number of lactation (X_2),days of milk (X_3), calving season (X_4), the first four test days records (X_5-X_8), and the 305-days milk yield (Y). MATLAB (Matrix Laboratory R2015), Statistical Package for Social Sciences version 21.0 Software for Windows (SPSS 21.0, Inc., Chicago, IL) and LINGO were used for the analysis of data.

In this study, the fuzzy linear regression method developed by Tanaka *et al*. (1982) was used to estimate 305-days milk yield of Jersey cattle at the beginning of the lactation. In the literature, the first fuzzy linear regression model, where the dependent variable is fuzzy and the independent variables are crisp numbers, was proposed by Tanaka *et al*. (1982). Fuzzy numbers are defined as fuzzy sets, which is identified in the real number set and expressed in fuzzy intervals (Baykal and Beyan, 2004; Lee, 2005). These numbers should be normal and convex. Additionally, the membership function needs to be partial permanent. Dubois and Prade (1980) suggested symmetric and non-symmetric triangular fuzzy numbers and trapezoidal fuzzy numbers to provide easiness in application. In the studies of Dubois and Prade (1978), Dubois and Prade (1979) and Dubois and Prade (1980), the representation of certain kind of fuzzy numbers defined in the form of L-R and descriptions related to algebraic operations were presented in detail. The primary aspect in creating fuzzy numbers in the form of L-R is to divide the central value of the fuzzy number in a left and right curve (Hanss, 2005).

The reference functions of fuzzy numbers are usually described as L or R. M represents the membership function in the L-R form of the fuzzy number. The equation is represented as following.

$$\mu_M(x) = \begin{cases} L\left(\frac{m-x}{\alpha}\right), \alpha > 0, x \le m; \\ R\left(\frac{x-m}{\beta}\right), \beta > 0, x \ge m, \end{cases} \quad [1]$$

There is a potential value interval of the output variable defined for the determined input in the system structure, and it can take any value in this interval. Fuzzy functions are used to express fuzzy coefficients, which are included in the model structure of fuzzy regression analysis (Tanaka *et al*., 1982; Ross, 2004). Fuzzy linear regression analysis is shown in Equation 2.

$$\tilde{Y}_i = \tilde{A}_0 + \tilde{A}_1 X_1 + \cdots + \tilde{A}_p X_{ip} \quad [2]$$

In the equation related to the fuzzy linear regression analysis, the parameter $\tilde{A}_j$ is stated with a fuzzy number and j represents the fuzzy coefficient. Membership functions play an important role in making predictions related to the possible values interval. Membership functions are formed by assigning every predicted value as a certain value of membership or belonging (Ross 2004). When $c_j > 0$, the parameter $\tilde{A}_j$ is expressed as $\tilde{A}_j = (\alpha_j, c_j)$, $j = 1, \dots, p$, $\alpha = (a_0, \alpha_1, \dots, \alpha_p)$ and $c = (c_0, c_1, \dots, c_p)$. Consequently, the Equation 2 can be restated in a more detailed way as shown in Equation 3.

$$\tilde{Y}_i = (a_0, c_0) + (a_1, c_1) X_1 + \cdots + (a_p, c_p) X_{ip} \quad [3]$$

The $\tilde{A}_j$parameter is defined as a fuzzy number with α_j as its center and c_j as its dispersion. In this case the value of centre is expressed as $\alpha = (a_0, \alpha_1, \dots, \alpha_p)$ and the dispersion is accepted as $c = (c_0, c_1, \dots, c_p)$. $c_j > 0$and represents the fuzziness of the dispersion function. $\mu_{A_i}$is defined for the independent variable coefficients and its membership function is shown in Equation 4 (Tanaka, 1982, 1989; Şanlı, 2005).

$$\mu_{A_j}(a_j) = \begin{cases} 1 - \frac{|\alpha_j - a_j|}{c_j}, & \alpha_j - c_j < a_j < \alpha_j + c_j \\ 0, & otherwise \end{cases} \quad [4]$$

With the help of the expansion principle defined by Zadeh (1965)$c_j > 0$, considering $\tilde{A}_j = (\alpha_j, c_j)$, $j = 1, \dots, p$ the membership function of the fuzzy number $\tilde{Y}_j$ is defined as shown in Equation 5 (Tanaka, 1982; Wang and Tsaur, 2000).

$$\mu_{Y_j}(y) = \begin{cases} 1 - \frac{\left|y_j - \sum_{j=1}^{p} \alpha_j x_j\right|}{\sum_{j=1}^{p} c_j |x_j|}, x \ne 0 \\ 1, \quad x = 0, y = 0 \\ 0, \quad x = 0, y \ne 0 \end{cases} \quad [5]$$

Here, $y_j$represents the output variable for the j^{th} observation and x represents the input variable.

The degree of fit of the predicted fuzzy output in the fuzzy linear regression analysis to the observed values of the dependent variable is represented by the h value (Ross, 2004). In other words, it is the cohesion measurement between the data and the regression model (Chang and Ayyub, 2001). This concept should not be confused with the goodness of fit in the ordinary regression analysis. The *h* value plays a considerably significant role in obtaining fuzzy parameters in the fuzzy linear regression analysis. Each of the parameters, which fall within the model in the fuzzy linear regression analysis, has a fuzziness degree. Errors are distributed to all model coefficients instead of solely one term. The *h* value is used to decrease fuzziness and indicates the degree of adaptation of the fuzzy output estimated in the fuzzy regression analysis (Icen, 2010; Moskowitz and Kim, 1993; Icen, 2010; Moskowitz and Kim, 1993). The *h* value is determined by the researcher before the analysis. This value is determined between the range of [0-1] and is integrated with the model as an input parameter (Tanaka *et al*., 1982; Moskowitz and Kim, 1993).

The aim of the model that was developed by Tanaka *et al*. (1982) is to obtain predicted values of fuzzy parameters through minimization of the dispersions in a certain *h* value (Tanaka *et al*., 1982). Tanaka benefitted from the model of linear programming to predict the fuzzy linear regression parameters. In order to provide the restriction in Equation 6, Equation 7 shows the linear programming to be used when the dependent variable is fuzzy.

$$Min\, c^t|X| = Min \sum_{j=1}^{p} c_j \sum_{i=1}^{m} |x_{ij}| \text{ or } \min_{c_j, c_j} J = c_1 + \cdots + c_p \quad [6]$$

$$c_j \geq 0$$

$$\sum_{j=1}^{p} \alpha_j x_{ij} + (1-h) \sum_{j=1}^{p} c_j |x_{ij}| \geq y_i + (1-h)e_i \quad [7]$$

$$\sum_{j=1}^{p} \alpha_j x_{ij} - (1-h) \sum_{j=1}^{p} c_j |x_{ij}| \leq y_i - (1-h)e_i$$

$$c_j \geq 0, \alpha \in \Re, x_{i0} = 1 \ (0 \leq h \leq 1;\ j = 1,2,\ldots,p$$

The fuzziness degree of the fuzzy linear regression analysis is expressed with the $J = c_1 + \ldots + c_p$ aim function. Here, the fuzziness degree is equal to the sum of the dispersion of the fuzzy parameters. The aim is to minimize the aim function.

In the analyses of the present study, the independent variables were included in the model as real numbers and the dependent variable was included as a fuzzy number. With the method developed by Tanaka *et al*. (1982) and grounded on the minimum fuzziness criterion, the fuzzy centre and fuzzy spread of regression coefficients were obtained by solving the linear programming problem. Eight independent variables (calving age (X_1), number of lactation (X_2), days of milk (X_3), calving season (X_4), the first four test days records (X_5-X_8)), and one dependent variable (305- days milk yield (Y)) were included in the fuzzy linear regression model of the present study. The construction of fuzzy regression analysis was performed using fuzzy outputs with crisp inputs. The fuzzy regression coefficients were included in the calculations as symmetric triangular fuzzy numbers. The *h* value in the analyses were set as "*h*=0.1, *h*=0.25, h=0.40,*h*=0.50, *h*=75, *h*=0.8, *h*=0.85, *h*=0.9, *h*=0.95 and *h*=1.0". The results of the analysis were compared with the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and coefficient of determination (R^2) values. The difference between observed and predicted milk yield values was analyzed by independent t-test.

RESULTS AND DISCUSSION

Table 1 shows the predicted parameter results of the fuzzy linear regression analysed with the different *h* values (0.1, 0.25, 0.4, 0.5, 0.75, 0.8, 0.85, 0.9, 0.95, 1). Analyses were conducted to obtain lower and upper regression curves for each *h* value with the use of the acquired results. Upon examining the parameter centre and spread values in Table 1, it was noticed that the parameter center at different *h* values were very close to each other and the spread of values were getting smaller. Using the parameter center and propagation values in Table 1, the upper and lower regression curves of the fuzzy regression model were obtained.

During the processes performed separately for each parameter, the estimated center and propagation values were collected to obtain the upper boundary curve. In order to obtain the lower bound curve, subtraction was performed with the estimated center and spread values. The obtained center values were the values estimated by the fuzzy regression model.

In Table 2, the error criteria values were calculated with the predicted centre values of the dependent variable and observed values, and their dispersion. Accordingly, the RMSE and MAPE values were found to be the highest with the *h* value of 0.8. Furthermore, they were calculated to possess the lowest trust and accuracy level of the data set and the degree of fit.

For the values *h* = 0.4 and *h*= 0.5, the lowest RMSE values were 42.4274 and 42.3350, the MAPE values were 0.0059 and 0.0059, and the coefficients of determination were calculated as 0.9337 and 0.9339, respectively. Moreover, the coefficient of determination and the other error criterion were very close values at *h*=0.4 and *h*=0.5. The observed milk yield mean (kg) and predicted milk yield mean (kg) were given in Table 2. The coefficient of determination revealed that all the *h* level values of the real values are at acceptable levels and the best goodness of values are at *h* = 0.4 and *h* = 0.5 level. The predicted milk yield mean values of the fuzzy linear regression equations developed for *h* = 0.4 and *h* = 0.5 values were found to be close to the observed milk yield mean values. The difference between the predicted values and the observed values were statistically insignificant (p>0.05).

Figure 1 illustrates the problems solved with the fuzzy linear programming method using different *h* values. The predicted lower and upper limits of the dependent variable, the observed real value, and predicted value are shown with four different regression curves. The analysis of the data set was conducted with ten different *h* values. The rational was to explore the degree of impact of the increase and decrease of the *h* value on the regression interval. All diagrams revealed that the observed values of the dependent variable were situated between the lower and upper regression curves. These results were found to be in line with the literature (Chang and Ayyub, 2001;Liu and Chen, 2013; Chen *et al*., 2016).

Therefore, *h*=0.5 or *h*=0.4 values were suggested for the data set of the present study. These were consistent with fuzzy linear regression studies in the literature (Tanaka *et al*., 1982; Bardossy, 1990; Liu and Chen, 2013; Chen *et al*., 2016)

The examination of the error criteria reported that the fuzzy linear regression equations obtained for the nearest realistic estimate of *h* = 0.4 (Equation 9) and *h*=0.5 (Equation 10) for the data set were used in this study (Table 2 and the Figure 1).

$$305DMY = (4064.568, 0) + X_1(-4.1589, 0) + X_2(56.6365, 0) + X_3(2.3011, 2.02) + X_4(-1.8601, 14.05) + X_5(13.2829, 0) + X_6(-13.9916, 0) + X_7(12.2969, 6.30) + X_8(23.5614, 24.30) \quad (9)$$

$$305DMY = (4017.207, 0) + X_1(-5.0047, 0) + X_2(67.5022, 0) + X_3(2.4878, 2.03) + X_4(1.6167, 11.93) + X_5(14.2101, 0) + X_6(-14.4032, 0) + X_7(12.6522\ 5.32) + X_8(22.6665, 20.76) \quad (10)$$

The results of the analysis revealed that the fuzzy linear regression analysis was considerably successful in making predictions of the 305-days milk yield with the variables of the test day milk yield, calving age, calving season, days of milk and number of lactation.

In this study, the main purpose of using fuzzy regression analysis is to create a prediction of 305-days milk yield and to express the dependent variable as a fuzzy number. Thus, by adapting the point of view indicated in the fuzzy logic theory to real world problems, it presents different aspects of perspective.

There are alternative methods used in the literature to estimate 305-days milk yield. Njubi *et al*., 2009 used milk control day records with 11 different models to achieve 305 g milk yield estimates. The results of the analysis showed that R^2 values were in the range of 0.444-0.790. In our study, the R^2 values for models developed for different *h* values ranged from 0.9258 to 0.9339 (Table 2). In Gorgulu's (2012) study, the artificial neural networks method was used to examine 305-days milk yield estimations. The analysis results showed that the artificial neural network method, which was alternatively recommended for regression analysis, could be successfully used. The results of the analysis revealed compliance with our work. Murphy *et al*. (2014) studied 305-days milk yield estimates using different milking day intervals using a static neural network (SANN), multiple linear regression model, and a nonlinear auto regressive model with exogenous input (NARX). The results of analysis using the mean absolute error, variance and root mean square error criteria showed that the methods used were very effective and could be used as an alternative to the traditional regression analysis, similar to the results obtained in our study.

Similar publications are included in the literature (Grzesiak *et al*., 2003; Sharma *et al*., 2007; Takma *et al*., 2012). Neural networks are a popular method of artificial intelligence in predicting 305-day milk yield and the prediction success is much higher than classical methods. However, it does not provide the point of view provided by the fuzzy regression. Presenting the dependent variable as a fuzzy number allows much more detailed analysis of the yield potential of the animals. The fact that learning performance in neural networks is highly dependent on the variable and number of observations increases the likelihood of network memorization and leads to a deviation of prediction accuracy. However, even when the number of observations is low in linear fuzzy regression analysis, the success rate is quite high. In addition, fuzzy regression also allows interpretation of different blur ratings and analyzes in accordance with the uncertainty environment assumed to exist in nature.

Table 1. The predicted parameter results of fuzzy linear regression.

h	X_0	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
0.1	(4163.07, 0)	(-2.70, 0)	(36.42, 0)	(1.89, 1.83)	(-7.57, 62.63)	(12.75, 0)	(-14.61, 0)	(12.98, 13.19)	(24.30, 84.85)
0.25	(4135.61, 0)	(-2.89, 0)	(40.3379, 0)	(2.0211, 2.009)	(-7.0754, 20.38)	(11.8671, 0)	(-13.3741, 0)	(11.7641, 9.24)	(24.9036, 34.90)
0.4	(4064.568, 0)	(-4.1589, 0)	(56.6365, 0)	(2.3011, 2.02)	(-1.8601, 14.05)	(13.2829, 0)	(-13.9916, 0)	(12.2969, 6.30)	(23.5614, 24.30)
0.5	(4017.207, 0)	(-5.0047, 0)	(67.5022, 0)	(2.4878, 2.03)	(1.6167, 11.93)	(14.2101, 0)	(-14.4032, 0)	(12.6522 5.32)	(22.6665, 20.76)
0.75	(3891.369, 0)	(-5.6537, 0)	(74.1331, 0)	(2.9583, 2.15)	(7.1914, 10.45)	(15.3926, 0)	(-14.5705, 0)	(12.7026, 3.81)	(21.3262, 14.44)
0.8	(3865.67, 0)	(-5.679, 0)	(74.0026, 0)	(3.052, 2.17)	(8.085, 10.35)	(15.546, 0)	(-14.5428, 0)	(12.6532, 3.61)	(22.1217, 13.54)
0.85	(3816.247, 0)	(-5.717, 0)	(73.728, 0)	(3.2339, 2.19)	(9.4807, 10.26)	(15.5655, 0)	(-14.2441, 0)	(12.5155, 3.43)	(20.8271, 12.75)
0.9	(3797.154, 0)	(-5.694, 0)	(73.5518, 0)	(3.3031, 2.21)	(9.0554, 9.86)	(14.7451, 0)	(-13.3981, 0)	(12.3349, 3.20)	(21.007, 12.10)
0.95	(3778.061, 0)	(-5.6723, 0)	(73.3757, 0)	(3.3722, 2.24)	(8.6301, 8.79)	(13.9247, 0)	(-12.552, 0)	(12.1542, 2.86)	(21.1869, 11.64)
1.0	(4135.61, 0)	(-2.89, 0)	(40.3379, 0)	(2.0211, 2.27)	(-7.0754, 7.81)	(11.86718, 0)	(-13.3741, 0)	(11.7641, 2.55)	(24.9036, 11.22)

Table 2. h values and statistical criteria for fuzzy regression models.

h	0.1	0.25	0.4	0.5	0.75	0.8	0.85	0.9	0.95	1
RMSE	44.3614	43.7261	**42.4274**	**42.3350**	*43.8042*	51.7168	43.9111	45.3617	45.4719	45.7029
MAPE	0.0062	0.00062	**0.0059**	**0.0059**	*0.0060*	0.0073	0.0060	0.0062	0.0062	0.0063
R^2	0.9291	0.9294	***0.9337***	***0.9339***	*0.9294*	0.9275	0.9264	0.9258	0.9265	0.9271
Observed Milk Yield Mean (kg)	5340.64	5340.64	**5340.64**	**5340.64**	5340.64	5340.64	5340.64	5340.64	5340.64	5340.64
Predicted Milk Yield Mean (kg)	5334.09	5339.03	**5341.81**	**5343.33**	5348.07	5368.86	5340.02	5351.11	5352.43	5353.72

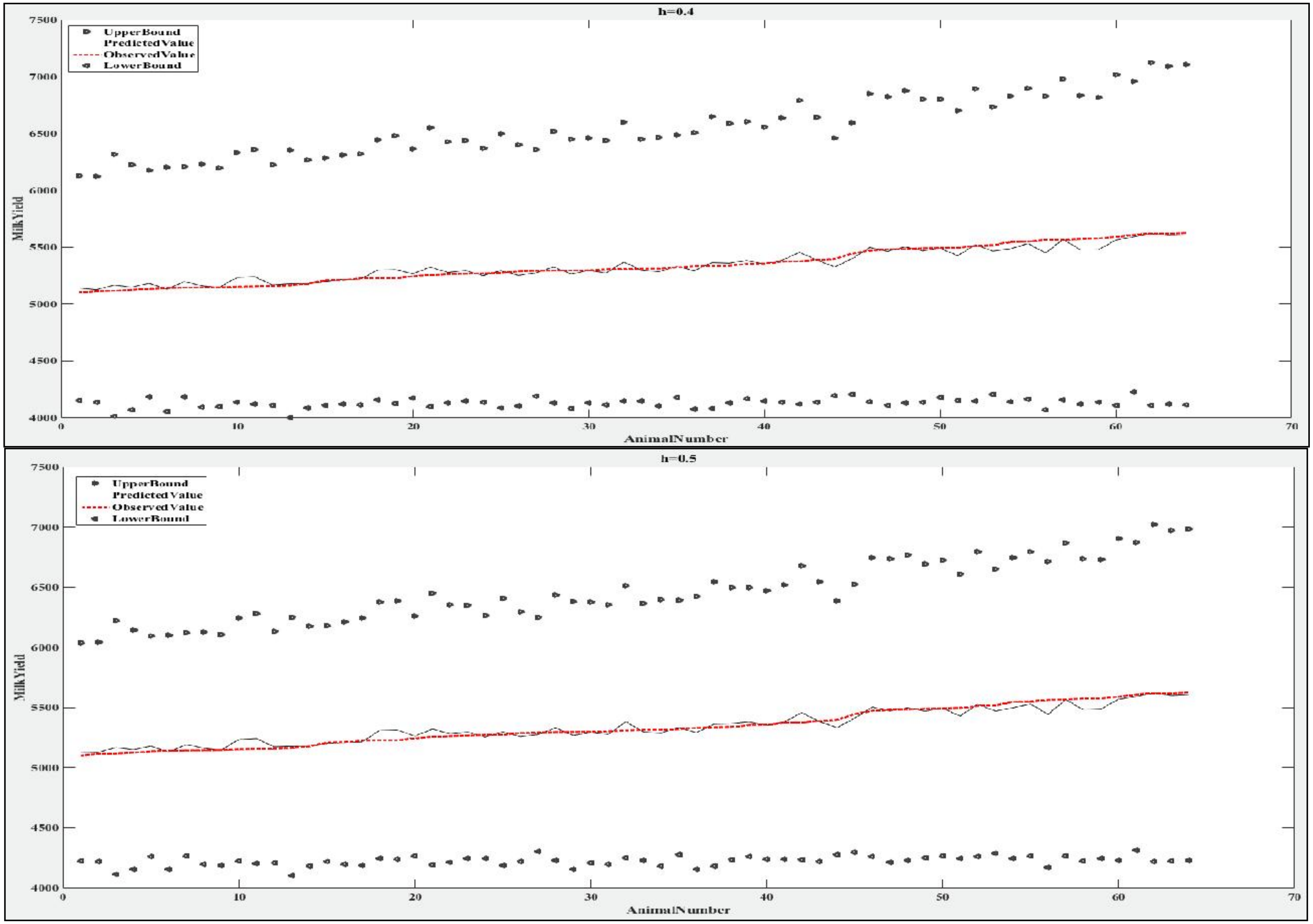

Figure 1. Results of h =0.4 and h=0.5 values in the fuzzy linear programming. In the all graphs. the upper line represents the upper bound; the lower line represents the lower bound.

Conclusion: Fuzzy linear regression analysis helps to produce successful assumptions in situations with uncertainty between variables and provides researchers with a flexible perspective. The fuzzy linear regression analysis is useful in the formation of meaningful prediction intervals in conditions with uncertainty and the providence of convenience to researchers during the prediction and decision-making stages. One of the major advantages of the fuzzy linear regression analysis is its independence from the assumptions of the ordinary regression analysis. Moreover, the non-influential values to the model are included in the analysis in the ordinary regression analysis. There are numbers of limitation of the fuzzy linear regression analysis. For instance, there is no certain formulation about how the *h* value should be, which is included in the model. In addition, the choice of the membership function is left to the researcher at the beginning of the analysis. In these situations, it is suggested to prefer the most successful one among the alternatives.

The present study explored the prediction on 305-days milk yield in dairy cattle with the use of fuzzy linear regression analysis. Being one of the fuzzy linear regression methods, the fuzzy linear programming technique was analyzed for this aim. The results of the analysis revealed that this technique can be successfully used in the prediction of 305-days milk yield at the beginning of the lactation.

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