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Research Article

A Fuzzy Logic Application to Predict Egg Production on Laying Hens [1]

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Abstract

Fuzzy logic has a great potential for researchers and it has been developed over the last two decades. In animal science, there are limited numbers of studies on fuzzy logic approach. This study was carried out to examine the Fuzzy logic applications for prediction of the egg production data. Egg production records were obtained from the commercial poultry farm in Izmir, Turkey. Egg production traits of brown laying hens at 22 to 40 weeks of age were analyzed with Fuzzy logic system. In this study, Fuzzy logic model was developed for the prediction of egg production values of three classes; top, middle and lower (bottom for the cage effect) production. For this purpose 120 data lines representing 4 inputs consisting of cage, age at sexual maturity (ASM), body weight at sexual maturity (BWSM), body weight at mature age (BW) and 1 output, egg production (EP) that collected daily and individually were used in a Fuzzy logic model. The similarities between predicted and original production records were investigated, the coefficient of determination (R^2) was found as 0.89 which was also shown the prediction's success rate. The probability of egg production at ASM of 168 days, BWSM of 1500 g and BW of 1820 g was found 98.97% while egg production's probability at ASM of 157 days, BWSM of 1720 g and BW of 1940 g was determined as 97.97%. These results were also concluded that layers reached at sexual maturity later have lower egg production. The results illustrated that Fuzzy model could provide an effective and accurate prediction for classifying egg production of laying hens. However, since the applications of fuzzy logic related to the prediction of egg production are limited, this work will be pioneered by future studies.

Keywords: *Artificial intelligent, Egg production, Fuzzy inference, Fuzzy logic, Poultry*

Yumurtacı Tavuklarda Yumurta Veriminin Tahminlenmesinde Bulanık Mantık Uygulaması

Öz

Yaygın bir çalışma alanına sahip olan bulanık mantık, son 20 yılda gelişmiştir. Hayvancılıkta bulanık mantık yaklaşımını kullanan az sayıda araştırma vardır. Bu çalışma, yumurta verimi kayıtlarının tahmininde bulanık mantık uygulamalarını incelemek amacıyla yapılmıştır. Yumurta verim kayıtları İzmir, Türkiye'de bulunan ticari kümes hayvanlarından elde edilmiştir. 22-40 haftalık yaştaki kahverengi yumurtacı tavuklara ait yumurta verim özellikleri bulanık mantık yöntemi ile analiz edilmiştir. Bu araştırmada bulanık mantık modeli; yüksek, orta ve düşük (kafes etkisi için alt) şeklinde üç sınıfta gruplandırılan yumurta verim değerlerini tahminlemek için geliştirilmiştir. Bu amaçla bulanık mantık modelinde kafes etkisi, eşeysel olgunluk yaşı (ASM), eşeysel olgunluktaki canlı ağırlığı (BWSM), ergin yaştaki canlı ağırlığı (BW) olmak üzere toplam 4 girdiyi temsil eden 120 veri satırı ile 1 çıktı değişkeni, günlük ve bireysel yumurta verimi (EP) kullanılmıştır. Belirtme katsayısı (R^2) 0.89 olarak bulunmuştur. Bu aynı zamanda tahminlemenin başarısını göstermektedir. Eşeysel olgunluk yaşı (ASM) 168. gün, eşeysel olgunluktaki canlı ağırlık (BWSM) 1500 g ve ergin yaştaki canlı ağırlık (BW) 1820 g olduğunda yumurtlama veriminin olasılığı %98.97 olarak bulunmuş iken eşeysel olgunluk yaşı (ASM) 157. gün, eşeysel olgunluktaki canlı ağırlık (BWSM) 1720 g ve ergin yaştaki canlı ağırlık (BW) 1940 g olduğunda yumurtlama veriminin olasılığı %97.97 olarak tespit edilmiştir. Elde edilen sonuçlar aynı zamanda geç yaşta eşeysel olgunluğa erişen yumurtacılarda yumurta veriminin daha düşük olduğunu göstermektedir. Bulanık mantık ile tahminlenen yumurta verimleri ile orijinal kayıtlar arasındaki benzerlikler araştırılmıştır. Bulgular, yumurta veriminin sınıflandırılmasında bulanık modelin etkili ve doğru bir tahmin sağlayabileceğini göstermiştir. Bununla birlikte, yumurta veriminin tahmini ile ilgili bulanık mantık uygulamalarının sınırlı olması yapılan bu çalışmayı daha sonra yapılacak çalışmalara öncü kılacaktır.

Anahtar sözcükler: *Yapay zeka, Yumurta verimi, Bulanık çıkarım, Bulanık mantık, Kanatlı*

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INTRODUCTION

In animal breeding studies, several methods have been developed to predict future yield by using available information of traits. Linear and nonlinear models are used as classical tools for this purpose. Artificial intelligent methods have also been introduced as an alternative to these classical approaches in recent years. Both mentioned approaches are used for mathematical description.

There are several applications of fuzzy logic in agriculture. In particular, in animal production studies it was used for the determination of oestrus cyclus, prediction of mastitis and culling levels [1-3]. Fuzzy logic also used in disease, weed and pest management as well as, soil analysis and developing expert systems for crops [4].

Nowadays, egg production has an important role in poultry industry. Besides genotypic structure; temperature, lighting, feeding and diseases have also direct effects on egg production [5]. North and Bell [6] implied that there was an increase in the 8^{th} or 9^{th} weeks of egg production while afterwards the production decreases at a constant rate [7]. Mashhadi et al.[8] invented an incubator, Olaniyi et al.[9] designed poultry feed and water systems, Abreu et al.[10] modelled the broiler performance in heat stress, and Bamigboye and Titus [11] applied temperature controlled systems in poultry houses by using Fuzzy logic method.

As far as we reached, there was no study carried out with the Fuzzy logic to predict egg production. So, in this study, for the first time, Fuzzy logic was examined to predict egg production.

MATERIAL and METHODS

Material

Egg production data from a commercial sire line in the 6^{th} generation were the material of the study. Brown layer hens were individually kept in three tiers double sided battery cages in an environmentally controlled hen house *(Fig. 1)*.

Table 1. *Descriptive statistics of scaled traits the developed Fuzzy Logic Model*

Traits	Rules Data Set (n=90)		
	Minimum	Maximum	Mean
ASM	125	198	152
BWSM	960	2160	1529
BW	1220	2540	1762
EP	37	131	108.81

ASM: age at sexual maturity, BWSM: body weight at sexual maturity, BW: body weight at mature age, EP: egg production

Egg production data were collected from the 22^{nd} to 40^{th} weeks of age defined as early part of whole egg production record. For each individual, egg production to the 40^{th} weeks of age (EP) was recorded and age at sexual maturity (ASM), body weight at sexual maturity age (BWSM), body weight at mature age (BW) were individually recorded, as well. The minimum, maximum and average values of the scaled input and output parameters are shown in *Table 1*. The modeling was performed by MATLAB (MatLab 2015b, The Mathworks, USA) software.

Methods

Fuzzy logic is a machine learning method that uses of human knowledge and experience to process this information into rule bases and to obtain the result that each rule base corresponds to a specific mathematical function. It is an artificial intelligence-based method that provides a realistic and flexible perspective to people, especially in decision-making processes. It depends on Aristotle's laws. In spite of Aristotle's "with or without

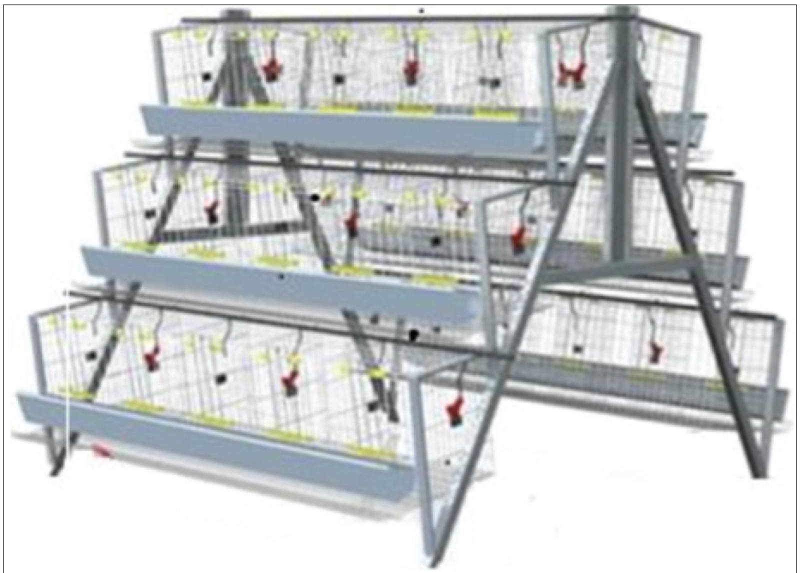

Fig 1. Three tiers battery cages double sided

laws"; Plato, on the other hand, has taken this situation forward and described a third situation in which right and wrong are internal, apart from being "right" and "wrong" [12,13]. Zadeh [14] explains the applicability of fuzzy logic to uncertainty-based systems and gave the name "Fuzzy Logic" in the name of the theory that these values are expressed in the range between 0.0 and 1.0 [14,15]. Zadeh [16] shows the concept of Fuzzy logic, which predicts to get rid of the limited movement and thought of the t wo-valued logic, with the Fuzzy set theory, which contains the truth values of an idea in infinite numbers between exact and definite truth [17].

Fuzzy logic; modeling in solving the problems due to multiple evaluations has advantages such as proximity to reality [18]. The first step of fuzzy logic is to define the problem and determine the appropriate parameters then forming the membership functions. Triangular, trapezoidal and Gaussian type membership functions from the membership functions in the Fuzzy library are compatible with the existing data set [19,20]. In this study, triangular type which gives the most appropriate estimation precision was used. Following the creation of membership functions, a chart of rules containing the solution of the problem was created. Then, inference methods, Sugeno, Mamdani and Tsukamoto were determined [21-23]. In this study Mamdani inference method was used.

The rule structure of this method is given as below,

If $X_1 = A_1$ and $X_2 = B_1$ then $Z_1 = C_1$

If $X_1 = A_2$ or $X_2 = B_2$ then $Z_2 = C_2$

where, X_1 and X_2 represent input variables; Z_1 and Z_2 represent output variables. A_1, B_1, A_2 and B_2 are membership functions, and C_1 and C_2 are the resultant set of fuzzy results for each rule. The "and" and then the "or" processors are used before the threshold values of the rules are calculated in the method of Mamdani inference [21,24].

In the last stage, the method of transforming the fuzzy numbers generated by a Fuzzy logic model into the classical numbers is determined [25]. An important step in fuzzy modeling and fuzzy decision making is the process of defuzzification which determines the best non-fuzzy performance value. Several methods for such defuzzification are available, including the mean of maxima (MOM), α-cut and center of area (COA) [26]. The MOM method that computes the average of those having the highest fuzzy outputs was used as the defuzzification method. The defuzzification value is computed as following [27].

$$Z = \sum_{j=1}^{n} \frac{Z_j}{n}$$

In the equation Z_j represents the output variable, n is the number of quantized and Z represents the defuzzication value that reaches their maximum memberships.

RESULTS

In the present study, both scaled (ASM, BWSM and BW) and discrete (cage) input variables were used for prediction of egg production to show more detailed solutions and relationships between egg production and scaled input variables.

It is necessary to determine the classes of the selected parameters and the range of the class before the fuzzification process which is the first step of the fuzzy system formation is started. Quality classes of input variables were determined by options of consulting experts. *Table 2* shows the quality classes and class ranges of the input variables; Cage, ASM, BWSM and BW.

Fig. 2 shows the Fuzzy logic model with 4 inputs on the left and 1 output on the right. Input variables consist of cage, age of sexual maturity (ASM), body weight of sexual maturity (BWSM) and body weight (BW). The output variable is egg production (EP).

Input and output variables of membership functions are shown in *Fig. 3-7*. All of the membership functions are displayed and edited to integrate the Fuzzy inference system, including both input and output variables.

After the membership functions were obtained in practice, a rule table was created. The Fuzzy rules were created by using the training algorithms with input-output variable pairs, and the Fuzzy rules were indicated in the IF-THEN form that was expressed the relation between machining performance and machining parameters [28,29]. It contains the real experiment results generated according to the characteristic change of the input parameters. Rules table consists of 76 rules. A part of the rule table is shown in *Table 3*.

Table 2. *Fuzzy sets for inputs*

Quality Class	Cage	ASM	BWSM	BW
Lower	0<x<1300	0<x<100	0<x<1100	0<x<900
Middle	1100<x<3100	80<x<3100	900<x<1600	800<x<1900
Top	3000<x<4128	140<x<198	1400<x<2160	1800<x<2540

ASM: age at sexual maturity, BWSM: body weight at sexual maturity, BW: body weight at mature age

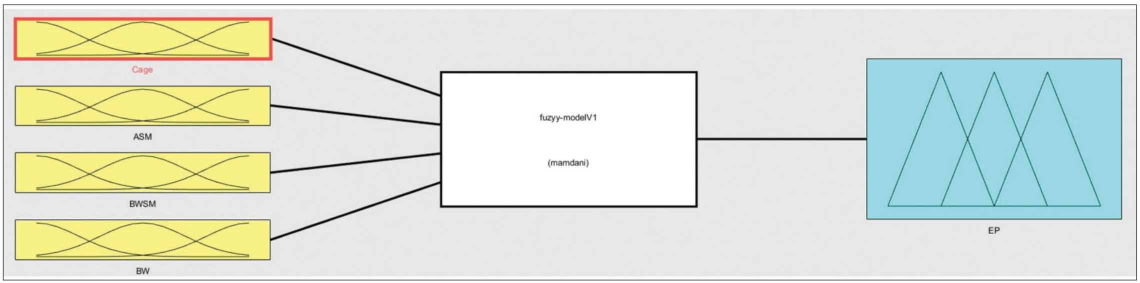

Fig 2. Fuzzy logic model

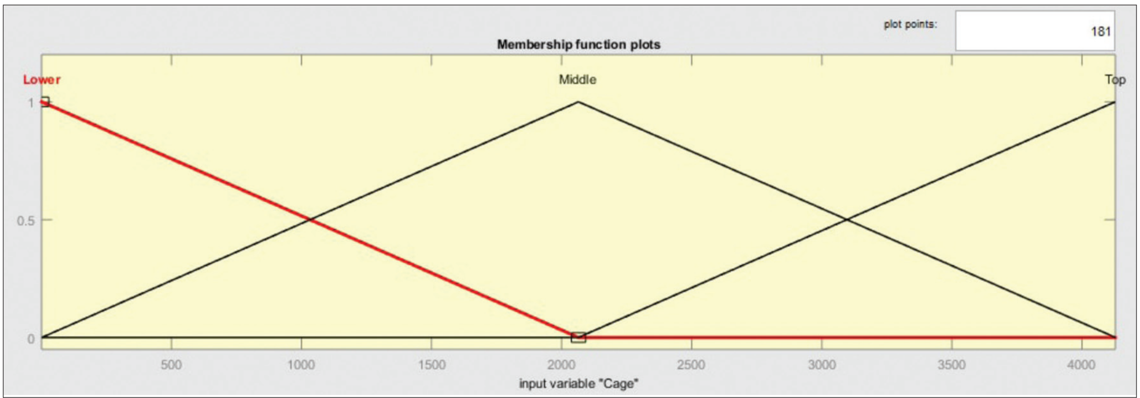

Fig 3. Cage membership function

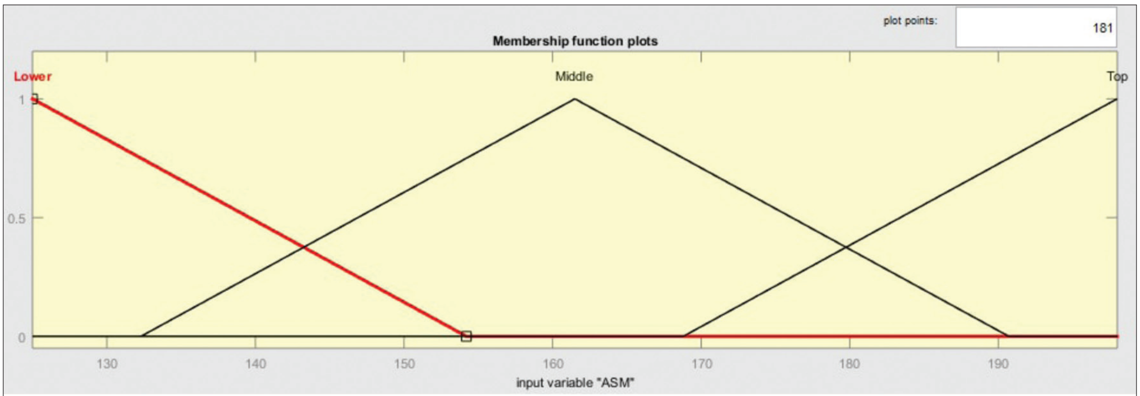

Fig 4. Age at sexual maturity membership function

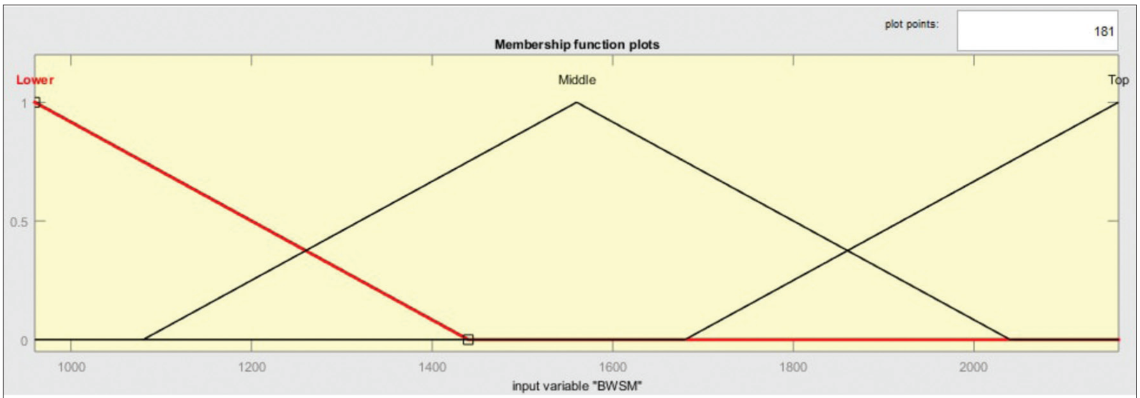

Fig 5. Body weight of sexual maturity membership function

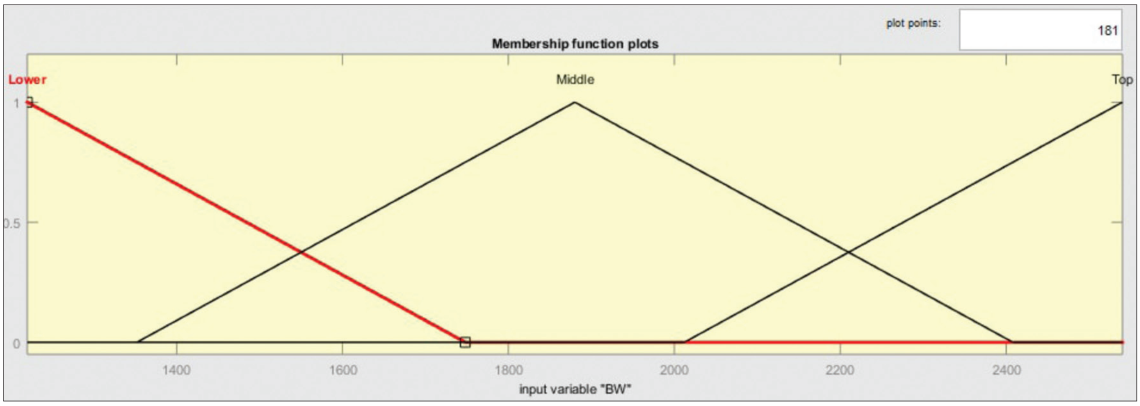

Fig 6. Body weight membership function

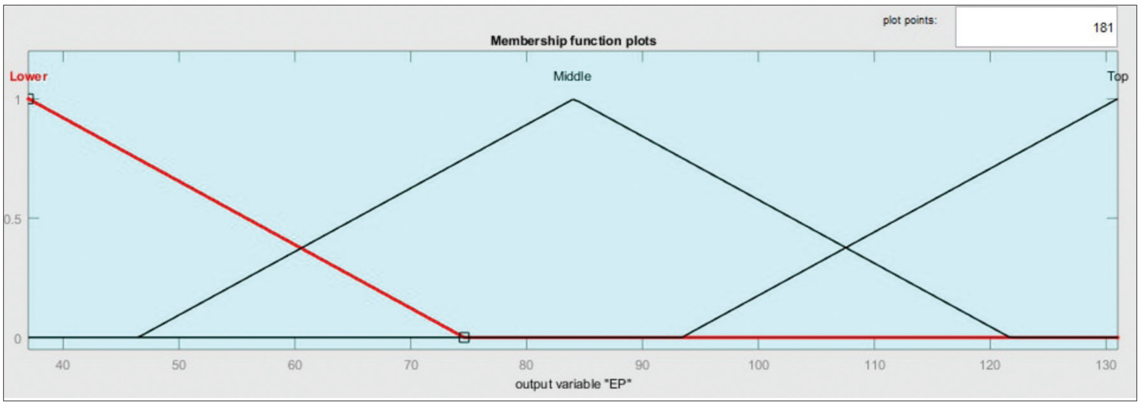

Fig 7. Egg production membership function

Table 3. *Fuzzy rule list*

Rule No	Rules
1	If (Cage is Lower) and (ASM is Middle) and (BWSM is Top) and (BW is Top) then (EP is Top) (1)
2	If (Cage is Lower) and (ASM is Middle) and (BWSM is Middle) and (BW is Middle) then (EP is Top) (1)
3	If (Cage is Middle) and (ASM is Middle) and (BWSM is Middle) and (BW is Middle) then (EP is Top) (1)
4	If (Cage is Lower) and (ASM is Top) and (BWSM is Middle) and (BW is Top) then (EP is Middle) (1)
5	If (Cage is Top) and (ASM is Middle) and (BWSM is Middle) and (BW is Middle) then (EP is Top) (1)
6	If (Cage is Top) and (ASM is Middle) and (BWSM is Middle) and (BW is Middle) then (EP is Top) (1)
7	If (Cage is Lower) and (ASM is Top) and (BWSM is Middle) and (BW is Middle) then (EP is Top) (1)
8	If (Cage is Top) and (ASM is Middle) and (BWSM is Top) and (BW is Top) then (EP is Top) (1)
9	If (Cage is Top) and (ASM is Middle) and (BWSM is Middle) and (BW is Middle) then (EP is Top) (1)
10	If (Cage is Lower) and (ASM is Top) and (BWSM is Lower) and (BW is Middle) then (EP is Top) (1)
11	If (Cage is Lower) and (ASM is Middle) and (BWSM is Middle) and (BW is Middle) then (EP is Top) (1)
12	If (Cage is Top) and (ASM is Top) and (BWSM is Middle) and (BW is Middle) then (EP is Top) (1)
13	If (Cage is Top) and (ASM is Middle) and (BWSM is Top) and (BW is Top) then (EP is Top) (1)
14	If (Cage is Top) and (ASM is Middle) and (BWSM is Middle) and (BW is Top) then (EP is Top) (1)
15	If (Cage is Lower) and (ASM is Middle) and (BWSM is Middle) and (BW is Middle) then (EP is Middle) (1)
16	If (Cage is Top) and (ASM is Middle) and (BWSM is Top) and (BW is Middle) then (EP is Top) (1)
17	If (Cage is Lower) and (ASM is Top) and (BWSM is Middle) and (BW is Top) then (EP is Middle) (1)

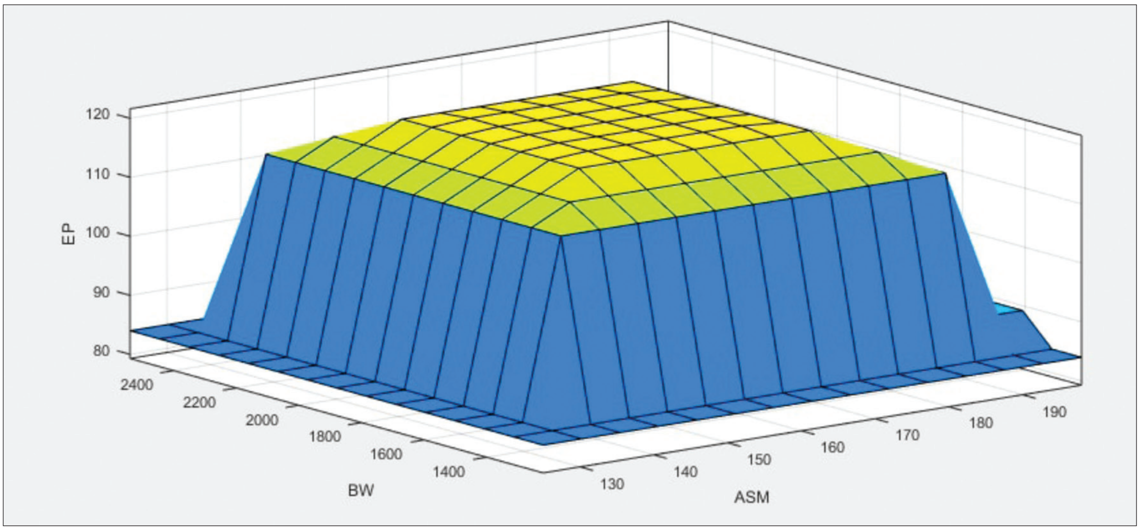

Fig 8. ASM-BW-EP correlation

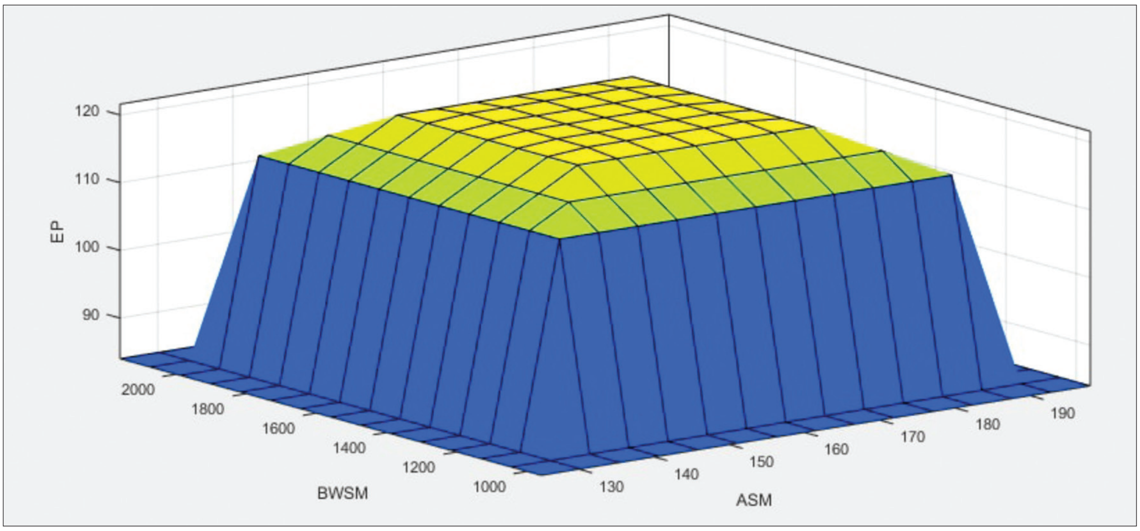

Fig 9. ASM-BWSM-EP correlation

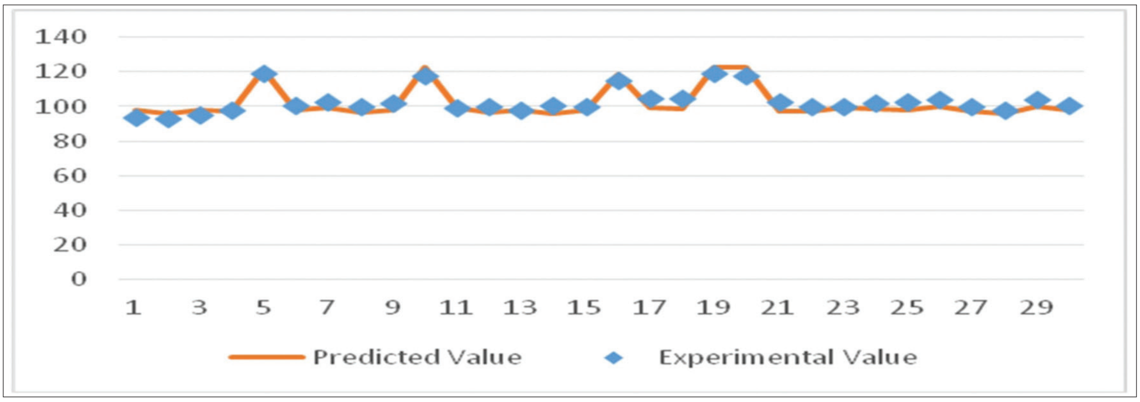

Fig 10. Comparisons of predicted results and observed results

There is surface viewer that shows a three dimensional (3-D) surface from two scaled input variables and one output variable of a Fuzzy inference system *(Fig. 8,9)*. The relationship among ASM, BW and EP is shown in *Fig. 8*

Table 4. *The analysis of results by using Fuzzy Logic Model*

Cage	ASM	BWSM	BW	Observed EP	Predicted EP	Classifications
299	155	1400	1700	94	97.96	TOP
3957	172	1540	1700	58	56.48	MIDDLE
687	171	1500	1720	95	97.96	TOP
883	163	1480	1760	98	97.25	TOP
342	167	1360	1600	101	96.57	TOP
687	171	1500	1720	73	72.68	MIDDLE
3192	154	1600	1860	87	88.54	TOP
170	168	1500	1820	99	98.97	TOP
291	146	1580	1800	100	96.58	TOP
650	164	1600	1520	67	68.00	MIDDLE
266	152	1440	1560	95	96.07	TOP
661	157	1720	1940	97	97.97	TOP

ASM: age at sexual maturity (days), BWSM: body weight at sexual maturity (g), BW: body weight at mature age (g), EP: egg production

while *Fig. 9* shows the relationship between ASM, BSWM and EP. It observed that the egg production as an output variable was effective at both values.

Fig. 10 compares the actual data with the data obtained from the Fuzzy logic model. Similarities between both data were investigated by the coefficient of determination (R^2). It showed that there was 89% success rate of the prediction, so the Fuzzy logic model was efficient in predicting the egg production. So, based on this high value of R^2, it can be said that, Fuzzy logic model is a powerful tool for the prediction of egg production. On the other hand, fuzzy models can also be used as an alternative tool to predict the whole record production from early part of egg production as a selection criterion to improve the whole egg production.

Some of the results by Matlab are given in *Table 4*.

Table 4 shows that the probability of egg production at sexual maturity of 168 days of age, body weight at sexual maturity of 1500 g and body weight of 1820 g was 98.97%. The probability of egg production at sexual maturity of 157 days of age, body weight at sexual maturity of 1720 g and body weight of 1940 g was 97.97%. Moreover, the probability of egg production at sexual maturity of 172 days of age, body weight at sexual maturity of 1540 g and body weight of 1700 g was 56.48%. It was obvious that layers reached at sexual maturity later have lower egg production.

DISCUSSION

Artificial intelligence studies have sought scientists to be able to think of machines as human brains. However, it has been observed that mental abilities such as intuition, non-monotonic and reasonable reasoning cannot be resolved with the classical logic understanding; therefore different studies have been made. The Decision support system is the one of those alternatives [24,29].

Fuzzy logic uses to achieve optimum solution of problems in engineering and agriculture. Similar to the findings of this study, researchers reported that Fuzzy logic could be used successfully in poultry. Fuzzy logic is a parallel structure to human thinking and in this parallelism the ability to recognize and determine systems has led to its rapid application areas. Poultry production is a well-developed and important industry in worldwide. The production of poultry meat and egg has been increased globally in years. However, there are still limited studies on Fuzzy logic systems in poultry, but no studies on egg production. Peruzzi et al.[30] used egg's physical characteristics such as egg weight, egg sphericity, eggshell thickness, and yolk per albumen ratio in Fuzzy logic modeling to estimate hatchability. Mehri [31] studied the factors affected hatchability in laying hens from 29 to 56 weeks of age. They used four inputs with 28 data lines including egg weight, egg sphericity, eggshell thickness and yolk/albumin ratio.

Artificial intelligence and its subfields such as machine learning are applied widespreadly in any scientific area in nowadays for any purposes such as pattern recognition or image classification. Fuzzy logic is an equal or sometimes faster method than the other applications for image classification since it is based on existed rules [32].

In animal science and veterinary medicine, there are limited numbers of studies about fuzzy logic. Some of those studies are related with diseases prediction, assessment of risks, designing equipments and controllers [33,34]. Artificial intelligence approaches like Fuzzy Logic can be initiated the expert's vision since they are included the information of experts. Because of this feature, fuzzy logic can be an alternative method for animal science related studies [24].

In conclusion, egg production is a complex process consisting of relationships among hormones, biochemical reactions and animal physiology with low heritability which means it is hard to predict and improve by individual selection. Low heritability also means that the trait is highly controlled by environmental factors more than the genotype. A Fuzzy logic model can be used for optimization of those effects. The method also shows its usefulness for predicting egg production in early weeks of the production period. Developing a Fuzzy logic model for prediction of egg production in earlier ages in hens has also an economic importance. It may give a chance to farmer to remove hens having low productivity at the beginning of the production period. Therefore, it can also be helpful for breeders in establishing new selection methods for traits having low heritability degree like egg production. Finally, it's thought that the Fuzzy logic has potential for fast, sensitive and realistic prediction values.

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