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Prediction of rabbit numbers in China with artificial neural networks

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Abstract
An Artificial Neural Network (ANN) model was created in this research to estimate and predict the number of rabbit in China. In the development of the ANN model, the years that are time variable were used as the input parameter, and the number of rabbit was used as the output parameter. The research data includes number of rabbit in China for 1961-2021 period. Mean Squared Error (MSE) and Mean Absolut Error (MAE) statistics were calculated using hyperbolic tangent activation function to determine the appropriate model. ANN model is a network architecture with 12 hidden layers, 12 process elements (12-12-1) and Levenberg-Marquardt back propagation algorithm. The number of rabbit was estimated between 2022 and 2030 with the ANN. As a result of the prediction, it is expected that the number of rabbit for the period 2022-2030 will be between 107 475 000-235 027 000.

Keywords: *Artificial neural network, neuron, rabbit, China.*

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I. INTRODUCTION

Small livestock species, including rabbits, have been promoted as tools in poverty alleviation programmes[1, 2].Rabbit is a prolific small mammal the origin of which is the Iberian peninsula and south of France [3].

Rabbit farming is in its infancy in Botswana. In agreement with Owen (1979) [4] who stated that in developing countries, the vast majority of meat rabbits are produced under small-scale or backyard systems, nearly all rabbit farmers in Botswana operate at subsistence level due to a number of factors including religious taboos and lack of knowledge on rabbit husbandry such as diseases and parasites [5].

It could been determined that the Bulgarian rabbit production was in extensive stage, but the legislation base was fully synchronized with requirement of European Union. In order to change it as intensive or semi intensive it need to improve selection and feeding systems, to concentrate the farm, and to build new more modern farms with control systems of microclimatic parameters and which covered veterinarian requirements[6].

In a study conducted in Kenya by [7], the most popular rabbit breeds were New Zealand white and the Californian rabbit due to their readily available breeding stocks and ability to multiply rapidly. Caged housing made of locally available materials was the most common. Low input feeding was common, with a majority of farmers using locally available forages with or without supplements. The main challenges included: rabbit diseases, lack of market for rabbits, poor breeding stocks, inadequate funds and insufficient feeds.

A rabbit enterprise or development project must be sustainable in all aspects or factors that comprise, guide or affect the production system. An appropriate small-scale rabbit production model (SSRPM) is proposed using a simple wheel analogy by [8]. In order to describe the spheres of the SSRPM, internal factors contain the production components, such as the suitability of breeding stock, availability of local resources or materials for housing and equipment, diet quality, health management, and other factors.

China has the highest number of rabbit in the world, in 2021.China ranked first in the world with 99169 000 numberof rabbit. Democratic People's Republic of Korea ranked second with 27019 000, and Egyptranked third with 6 680 000 [9].

The aim of this study is to model and forecast the presence of rabbits reared in China using artificial neural networks.

II. MATERIAL AND METHOD

The data used in the study formed the number of rabbit under the title of "Crops and livestock products" compiled from the www.fao.org website of the United Nations Food and Agriculture Organization [9]. In the study, data between 1961 and 2021 were used and analyzed with artificial neural networks (ANN). After the appropriate model was determined, the number of rabbitbetween 2022-2030 was predicted.

The method demonstrated in this division can be applied efficiently to provide number of rabbit forecasts. The adequacy of observed number of rabbit data makes it possible to use this method for prediction. To formulate an ANN with high prediction accuracy that generalizes well, it is necessary to consider several issues, especially the design and training parameters.

In this research, [-1, 1] data normalization was selected. The process of data normalization using the minimum/maximum method employed is demonstrated in below [10].

$$x^{'} = \frac{x - Min(x)}{Max(x) - Min(x)} + \left(newMax(x) - newMin(x)\right) + newMin(x)$$

where$x^{'}$ is the new value, x is the old value, and min(x) and max(x) are the minimum and maximum values of attribute x, respectively. All noted that transform sample outputs are in the domain of [-1,-1] former to ANN training.

One of the activation functions, the tangent sigmoid (tansig) function was performed.The tansig function is expressed as [11].

$$tansig(x) = \frac{2}{1 + e^{-2x}} - 1$$

In order to train the ANN, number of rabbit parameter measured in China for the last 60 years (1961–2020) were utilized for training and testing. During the training process, the weights were adjusted to make the actual outputs (predicted) close to the target (measured) output of the network, as mentioned in the previous section, using the L-M algorithm in accordance with the mean squared error (MSE).

To evaluate the precision of the predicted discharge volume, Mean Square Error (MSE) and Mean Absolute Error (MAE) were calculated [12, 13].

$$MSE = \frac{\sum_{i=1}^{n}(y_i - y_{ip})^2}{n}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|(y_i - y_{ip})\right|$$

Here, y_i is the observed value of the dependent variable (number of mule), y_{ip} is the predicted value of the dependent variable (number of rabbit) and n is the number of samples.

III. RESULTS AND DISCUSSION

The number of input, hidden and output layers was determined as 12-12-1, respectively, with ANN. It was applied with back propagation learning with 1000 iterations. The hyperbolic tangent activation function was used for number of rabbit in ANN method. The lowest MSE=140381068.008and MAE=8704.184were obtained in ANN management for number of rabbit.

Table 1 indicates the estimated and observed values as a consequence of the ANN method together with the error terms values. Figure 1exhibits the graph of the progression and distribution of the real and predicted values as a consequence of the ANN application for number of rabbitprediction.

Table 1. Observed, estimated and residual values

Years	Actual (1000 Head)	Predicted (1000 Head)	Residual
1990	155172	164212,253	-9040,2534
1991	162161	165892,563	-3731,5626
1992	165139	169659,639	-4520,6388
1993	175128	169136,715	5991,2854
1994	185112	170680,944	14431,056
1995	149469	172231,339	-22762,339
1996	155079	146044,64	9034,3601
1997	160076	170866,327	-10790,327
1998	168055	159821,683	8233,3175

1999	175055	183747,06	-8692,0601
2000	185043	194711,987	-9668,9871
2001	190040	188740,721	1299,2793
2002	191289	191371,874	-82,8735
2003	194259	207128,021	-12869,021
2004	196641	201827,246	-5186,2464
2005	202196	201242,573	953,4267
2006	217678	212547,279	5130,7214
2007	213187	211254,171	1932,8294
2008	202038	204215,394	-2177,3939
2009	210040	197066,389	12973,611
2010	218040	204809,853	13230,147
2011	220050	206855,451	13194,55
2012	225055	209663,565	15391,435
2013	223513	212101,877	11411,123
2014	222806	204049,016	18756,984
2015	216095	207571,66	8523,3402
2016	168243	205086,819	-36843,819
2017	121207	146932,53	-25725,53
2018	120415	109682,18	10732,82
2019	119458	122484,108	-3026,1075
2020	109255	108170,515	1084,4854
2021	99169	100810,479	-1641,4788

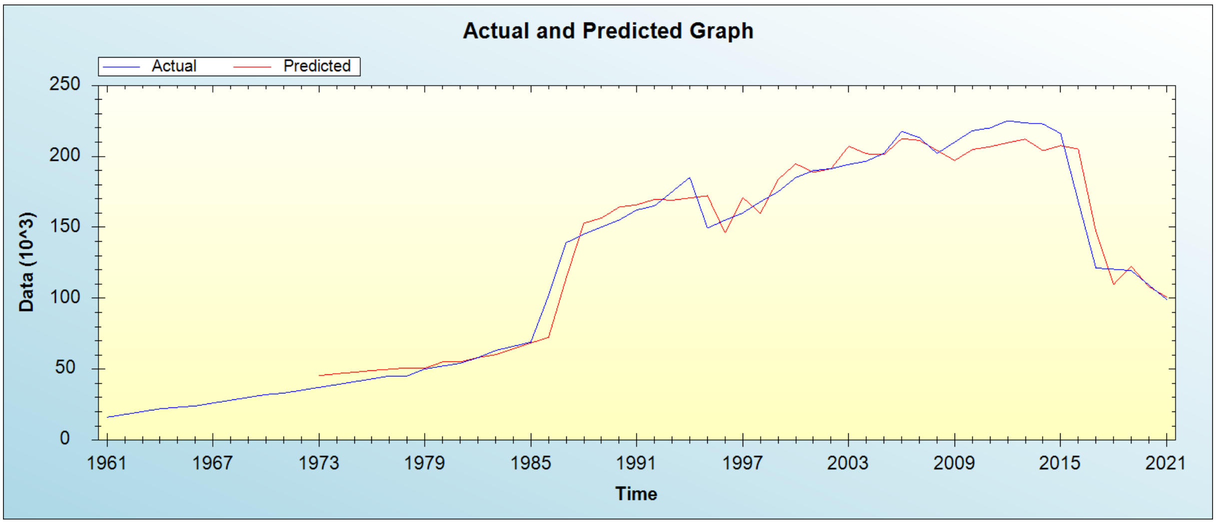

Figure 1. Graph of observed and predicted values

Figure 2indicates the graph of the error terms obtained by the ANN method andin Figure 2, it is seen that the error terms are distributed randomly.

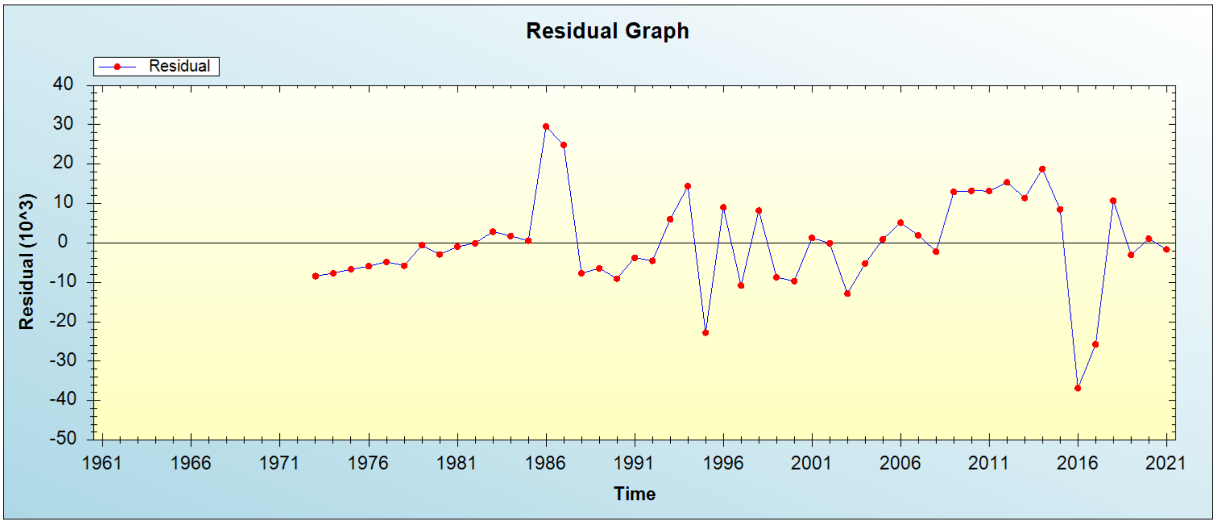

Figure 2. Graph of residual values

Figure 3 shows the graph of the number of rabbitobservation values and error terms. Real values and error terms are distributed randomly and are independent from one another.

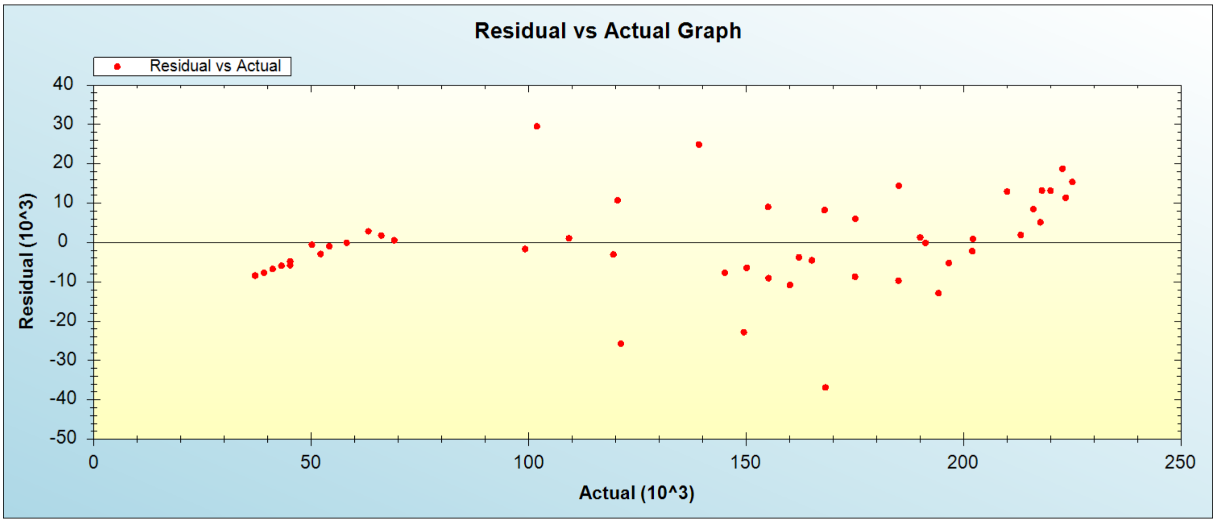

Figure 3. Graph of actual values and residual values

Subsequent this, a prediction for number of rabbit in the following years was made. In Table 2 and Figure 4, the predictednumber of rabbit for the years 2022 to 2030 is display.

Table 2. Forecast of number of rabbit for the next periods

Years	Forecasted
2022	104 513 772
2023	116 355 645
2024	127 504 792
2025	133 414 365
2026	121 625 813
2027	132 103 177
2028	173 783 287

2029	195 078 378
2030	196 791 828

As seen in Table 2, it is anticipated that there will be a constant increase in the number of rabbit in the nine-year period from 2022 to 2030 in China. The number of rabbit, which was 99169 000 in 2020, is predicted to rise by 98.44% to 196791828 in 2030.It is expected that the maximum number of rabbits will be in 2030 with 196791828.

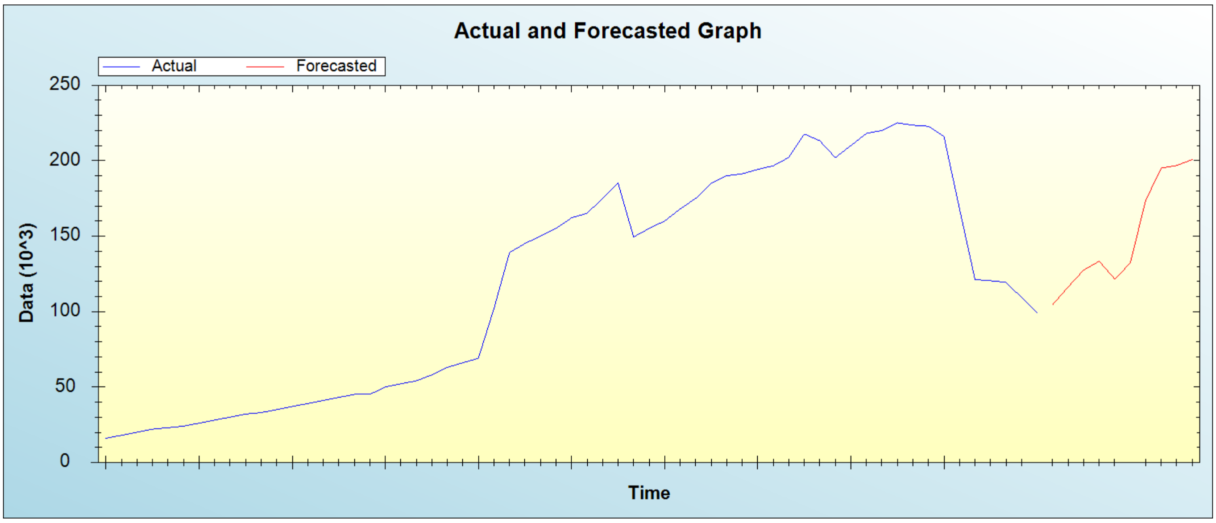

Figure 4. Actual values and forecasting for the future

[14]statements that inadequate funds and restricted information are the main factors hindering commercialization in Kenya.

There are some studies in the field of livestock that employed artificial neural networks and time series. For instance, ANN was used to forecasting the number of camel, pig, donkey and mule [15, 16, 17, 18].

IV. CONCLUSION

In this study, the number of rabbit in China was modeled with artificial neural networks. The hyperbolic tangent function, one of the activation functions, was used. The lowest possible MSE and MAE values were obtained in the training, testing, and validation stages.

With the ANN analyzed using the hyperbolic tangent function, the number of rabbit in China is predicted to range between 104513772and 196 791828in the period of 2022–2030. Number of rabbitwaspredicted to rise in the next 9-year period compared to 2020. After 9 years, this increase is expected to be 99.44% in 2030. It is expected that employing artificial neural networks and alternative methods in future forecasting studies could result in important results for livestock data.

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