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Comparison of five mathematical models that describe growth in tropically adapted dual-purpose breeds of chicken

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ABSTRACT

Mathematical models provide valuable information for livestock improvement programmes. In this study, we evaluated the ability of five mathematical models (3P and 4P Gompertz, 3P and 4P logistic and neural network) to predict the growth of six tropically adapted dual purpose (TADP) chicken breeds (Fulani, FUNAAB Alpha, Kuroiler, Noiler, Sasso and Shika-Brown) under on-station and on-farm in Nigeria. Data for body weight were collected every 14 days from 1939 birds reared on-station, and every 28 days from 58,639 birds reared on-farm. Parameters used to evaluate the growth models were the adjusted coefficient of determination ($AdjR^2$), Akaike's information criterion (AIC), Bayesian information criterion (BIC) and root mean square error (RMSE). The $AdjR^2$ for Gompertz 3P was higher than or equal to the $AdjR^2$ for logistics 3P, Gompertz 4P and logistics 4P but was equal to or lower than the $AdjR^2$ for the neural network (NN) for all TADP chickens raised on-station. Based on the goodness-of-fit criteria, Gompertz 3P had the best predictive values ($AdjR^2 = 0.989–0.998$) for TADP chickens raised on-station, while logistic 3P was the best-fit model for TADP chickens raised on-farm. In conclusion, non-linear models and NN models yielded a good fit with the age-weight data of TADP chickens on-station and on-farm.

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Introduction

Indigenous chickens contribute immensely to food security and livelihoods of smallholder farmers in the tropics. Despite being inferior to broilers in body weight, indigenous chickens are preferred for their survivability, disease resistance, meat quality and scavenging ability. Growth, defined as an increase in body size, is a defining parameter of biological systems (Lawrence and Fowler 2002). Body weight is one of the most significant traits in poultry production because it is associated with growth rate, feed conversion efficiency and occurrence of diseases in a flock (Amraei et al. 2017). Poultry growth patterns have been predicted using different mathematical models (Darmani et al. 2003; Sengul and Kiraz 2005; Roush and Branton 2006; Yaya et al. 2019). Several factors both non-genetic (health, age, welfare, location and feed) and genetic (breed or strain) have been implicated in the huge variations in growth curves fitted to the mathematical models (Darmani et al. 2010).

The application of mathematical models to fit data to the growth curve in chickens provides parameters that are used to predict body weight at a specific age and to detect the beginning of the reduction in growth rate (Yakupoglu and Atil 2001). Such analysis of the growth curve is highly desirable in developing countries to assist in the quest for maximization of genetic gains for improved performance in livestock production and attainment of animal protein sufficiency (Abbas et al. 2014).

Mathematical modelling is useful for optimizing growth rate, livestock performance, slaughter age, appropriate feeding and selection (Sariyel et al. 2017). A useful growth model should be parsimonious and contain parameters that have biological and physical meaning (France et al. 1996). The age–weight relationship has been described by many mathematical models such as logistic model (Grossman and Bohren 1985; Tsoularis and wallace 2002), Richard model (Knizetova et al. 1991) and Gompertz model (Barbato 1991; N'dri et al. 2006).

In many studies of Japanese quail growth data, Gompertz, logistic or von Bertalanffy growth models were used (Tzend and Becker 1981; Akbaş and Oğuz 1998; Alkan et al. 2009; Narinç et al. 2010; Narinç and Aygün 2010; Alkan et al. 2012). A common characteristic of these models is the fixed inflection point. The body weight at the inflection point is identified as 37% of the asymptotic weight in both the Gompertz and von Bertalanffy models and 50% in the logistic

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model. In fixed growth models, the genetic variations of asymptotic weight and point of inflection weight are equal, which constitute a problem for genetic improvement (Darmani et al. 2010).

Analyses of broiler growth data using the Gompertz growth models result in a single sigmoidal curve (Wang et al. 2004; Strathe et al. 2010). Santos et al. (2005) used the Gompertz model to analyse growth in two slow-growing broiler lines housed in two different systems. Dourado et al. (2009) used the Gompertz model to examine the growth of slow-growing broilers reared in the free-range system. Gompertz, logistic and Richard models were used by Norris et al. (2007) to analyse the body weight of indigenous Venda and Naked Neck chickens of South Africa and growth curve parameters were estimated and compared.

Several studies, estimating the biological parameters of the growth curve for chickens, have been reported. Knizetova et al. (1985) observed age at inflection point values of 63.7, 79.8 and 81.5 days for White Cornish, White Leghorn and New Hampshire cockerels, respectively. The logistic and Gompertz models have been extensively used in poultry production for on-the-spot assessment of body weight changes and nutritional challenges (Gous et al. 1999; Darmani et al. 2003; Sakomura et al. 2005) because of their robust nature in modelling growth curve patterns. Yapi et al. (2011) observed that indigenous chickens took longer (51.22 days) to reach the point of inflection than the commercial genotypes (50.68 days for C-Nana and 46.91 days for C-nana). Ait and Moula (2013) reported maturation growth rate (K) of 0.0260 and 0.0294 g d^{-1} for the chickens of Kabyle in Algeria, whose values were superior to the values of 0.0189 and 0.0205 g d^{-1} reported by Yapi et al. (2011) for the indigenous chickens in Cote d'Ivoire.

Both Gompertz and logistic models belong to the Richards family of three-parameter sigmoid growth models (Tjørve and Tjørve 2017), which have been reported to be adequate in explaining weight growth in chickens (Zhao et al. 2015; Michalczuk et al. 2016).

The Neural network model learns the growth parameters of algorithms automatically from data without resorting to the underlying biological basis of the equation. Its ability to cope with high inputs of data, non-linearity and prediction accuracy of 98–99% is an indication that it can successfully replace the conventional methodologies (Sivanandam et al. 2008; Milosevic et al. 2019). Also, it belongs to the group of high-resolution models, and its flexibility makes it a generalized alternative to Gompertz and logistic equations (Thornley and France 2007; Ahmad 2009). Safari et al. (2017) observed that neural network models are more efficient and reliable in describing the relationship among parameters than non-linear regression models.

In meat type chickens, an appropriate body weight is required for optimal production at the end of rearing. Mathematical models have been used to fit growth models, where biologically relevant parameters could be related to performance, such as asymptotic weight (Teleken et al. 2017). These models have three or four parameters and at least one parameter of the model has a biological meaning (Iqbal et al. 2019). Selvaggi et al. (2015) reported that Gompertz 3P model fitted live weight data more appropriately for male and female birds than the 4P models in non-descript Italian chicken breeds. However, most studies have only explored 3P models with a single asymptote in fitting the growth curves of indigenous and exotic chickens. These models are prone to overestimation of predicted data, thereby leading to erroneous inferences in estimating genetic gain in breed improvement programmes. However, the use of 4P versions of logistic (Liao and Liu 2009) and Gompertz (Wellock et al. 2004; Porter et al. 2010) models might minimize overfitting of the curves.

Studies comparing mathematical models for chicken growth, using 3P logistic and Gompertz models, have been widely reported in the literature (Thornley and France 2007; Zhao et al. 2015; Michalczuk et al. 2016). However, studies, comparing the predictive ability of 3P Logistic and Gompertz models and their 4P versions with neural network model in TADP chickens, under both on-station and on-farm conditions, have not been reported. This is the purpose of this report.

The aim of this study was to assess the predictive ability of different mathematical models (3P and 4P Gompertz, 3P and 4P logistic and neural network) for forecasting the growth of TADP chickens at 0–20 weeks under on-station and on-farm conditions in Nigeria. We hypothesize that models that are parsimonious under on-station conditions will also be under on-farm conditions. In addition, we expected to observe sexual dimorphism in TADP chickens for sigmoid growth patterns.

Materials and methods

Experimental site

The on-station test was conducted at Fol-Hope Farms, Ibadan, Oyo State and the Federal University of Agriculture, Abeokuta (FUNAAB), located within the Southern Guinea Savanna, and Dry Lowland Rainforest agro-ecological zones, respectively. The testing of the birds commenced in May 2016. The on-farm test was carried out in five agro-ecological zones as follows: Kebbi State (Sudan and Northern Guinea Savanna), Kwara State (Southern Guinea Savanna), Nasarawa State (Southern Guinea Savanna), Imo State (Wet Lowland Rain Forest and Fresh Water Swamp) and Rivers State (Mangrove Swamp and Fresh Water Swamp).

Management systems

A total of 1939 d-old chicks of both locally sourced breeds (Fulani, FUNAAB Alpha, Noiler and Shika-Brown) and imported breeds (Kuroiler and Sasso) were brooded to 42 days (Table 2). The birds were sexed at 42 days, and males and females were grown separately until 140 days under station (intensive production system) conditions. The stocking density was 10 chicks/m^2, seven birds/m^2, and five birds/m^2 during 0–42d, 43–91d and 92–140d, respectively. Commercial feed (Chick mash at 0–42d: 2,993 kcal ME/kg, 22.3% CP and Grower mash at 43–140d: 3013 kcal ME/kg, 17% CP) and water were available *ad libitum*. Birds in both stations were fed the same proprietary feed. Standard biosecurity measures and vaccination schedules were observed at the test centres. Body weight was measured every two weeks. For the on-farm test, a total of 58,639 six-weeks-old pre-vaccinated chickens were distributed to 2100 households across five states representing different agro-ecologies (Table 3). Standard backyard scavenging management practices were followed by the farmers with the addition of overnight housing, feed supplementation and vaccination programmes. Body weight was taken every four weeks.

All applicable veterinary permits were obtained for the importation and use of the imported breeds for research purposes (Bamidele et al. 2019). Both the on-station and on-farm studies were approved by the International Livestock Research Institute (ILRI) Institutional Research Ethics Committee (IREC) with reference no.: ILRI-IREC2015-08/1, and ILRI Institutional Animal Care and Use Committee (IACUC) with reference number: ILRI-IACUC-RC2016.2. Each farmer gave written informed consent to participate in the study.

Table 2. Allocation of strains of chickens tested on-station in Nigeria.

Station	Breed	Number
IBADAN, Fol-Hope farms	Kuroiler	204
	Sasso	204
	Fulani	50
	FUNAAB Alpha	170
	Shika-Brown	200
	Noiler	150
ABEOKUTA, FUNAAB Poultry Unit.	Kuroiler	204
	Sasso	204
	Fulani	20
	FUNAAB Alpha	183
	Shika-Brown	200
	Noiler	150
Total		1939

Table 3. On-farm experimental allocation of households in Nigeria.

Strain	No. of batches of distribution	No. of HH/ breed/ State	Total no. of households per breed	Ave. no. of birds per household
Fulani	5	36	180	20
FUNAAB Alpha	5	48	240	20
Kuroiler	2	84	420	25
Noiler	1	84	420	20
Sasso	1	84	420	25
Shika-Brown	2	84	420	25
Total		420	2,100	

Notes: HH: household; Ave: average.

Statistical procedures

Repeated measures of individual body weight at different ages of males and females' TADP chickens were fitted to 3P and 4P models, respectively. The 3P models sought to fit a response that is between zero and the estimated asymptote. The 4P models sought to fix a response between zero and two estimated asymptotes. The models used in fitting the growth curves are presented in Table 1.

Neural network computations

The whole datasets for body weight and age were separated at random into two subsets (training and testing) using a supervised neural network. The training set consisted of 75% and testing subset consisted of 25%. The training sets were used to train the neural network models, and the testing sets were used to validate the models. The networks were tested with 100 hidden layers with 320 neurons in each hidden layer to optimize the body weights. Initial weights and bias matrix were randomly initialized between −1 and –1. We used a non-linear transformation (or activation) models tangent sigmoid as shown below

$$f^{(x)} = \frac{1}{1 + e^{-\alpha x}}$$

to compute the output from the summation of weighted inputs x of neurons in each hidden layer, where α is a constant. A pure linear transformation model was used as an output layer for getting network responses (Sivanandam et al. 2008).

We implemented both the specialized modelling technique (SMT) and the predictive modelling technique (PMT). The SMT adopts the fit curve procedures which contain varieties of inbuilt, non-linear models using ordinary least squares methods, while the PMT was used to train, test and validate the neural network for estimating or forecasting age–weight relationship.

Breed and sex effects were estimated using the general linear model to compute the summary statistics (Means ± SD). Significant differences in means were separated using Tukey test. The growth models (3P and 4P Gompertz; 3P and 4P logistic) were fitted to the measurements of actual body weight related to age via a non-linear procedure, using the Marquardt algorithm of J.M.P 13.2 statistical software. On the other hand, the two-layer fully connected multilayer perceptron algorithm procedures were used to model the neural network using default random holdback methods which was set at 0.3333

Table 1. Equations of the non-linear regression growth curve models.

Model	Equations	Age at inflection point	Weight at inflection point
Gompertz 3P	$Y = a.\exp(-\exp(-b.(age - c)))$	$\ln\frac{b}{a}$	$\frac{c}{e}$
Logistic 3P	$Y = \frac{c}{(1 + \exp(-a \cdot (age - b)))}$	$-\ln\left(\frac{1}{b}\right)^{-a}$	$\frac{c}{2}$
Gompertz 4P	$Y = a + (b - a) \cdot \exp(-\exp(-c \cdot (age - d)))$	$\ln\left(\frac{d}{a}\right)$	$\frac{a}{e}.c$
Logistic 4P	$Y = c + \frac{d - c}{(1 + \exp(-a \cdot (age - b)))}$	$\frac{c + d}{2}$	$\frac{d}{2}$

Notes: Y is the estimated weight at age x; a is the maturity index; b is the scale parameter; c is the asymptotic weight; d is the upper asymptote; Gompertz 3P was referenced from Gompertz (1832); Logistic 3P from Darmani et al. (2010); Logistic 4P from Ratwosky and Reddy (1986); Gompertz 4P from Tjørve and Tjørve (2017).

with hidden nodes of 1000. The models' performances were compared based on the $AdjR^2$, RMSE, AIC and BIC. RMSE and $AdjR^2$ of the models were considered as the calculated goodness-of-fit parameters for comparing the different models across breeds of TADP chickens. We obtained AIC using $n \cdot \ln(\mathrm{SSE}/n) + 2k$, where n is the number of observations, SSE is the sum of the square of errors, and k is the number of parameters. We derived BIC using $n \cdot \ln(\mathrm{SSE}/n) + 2k \cdot \ln(n)$. Estimated mean parameters obtained from different models were used to plot the general growth curves of the TADP chickens.

Results and discussion

Results on growth performance of the TADP chickens raised on-station, and on-farm have previously been reported by Bamidele et al. (2019), and Ajayi et al. (2020), respectively. Estimated growth curve parameters of male and female birds raised on-station are presented in Tables 4 and 5, respectively. Different growth models of the six TADP chickens used in this study showed variations in estimated asymptotic weight. The TADP chickens had higher upper asymptotic weight, except for logistic 3P (1332.09 g) and 4P (1408.14 g) in Fulani which was lower, than the Lohmann average of 1500 g of body weight for laying hens. The weight at the inflection point was lower than the upper asymptotic weight for all the TADP chickens. The earlier occurrence of the maturity rate in Gompertz than in logistic models implies that the Gompertz model is more sensitive to growth response. The asymptotic weight represents the maximum growth response for animals which are mostly affected by genotype and environment interactions (Narinç et al. 2010). The weight at the inflection point was above 1000 g for all TADP chickens except for Fulani and Shika-Brown. Noiler had the lowest scale parameters (5.22 weeks, Gompertz 4P and 9.54 weeks, logistic 3P) followed by Kuroiler (8.83 weeks, Gompertz 3P and 10.14 weeks, logistic 3P), Sasso (9.76 weeks, Gompertz 3P and 10.92 weeks, logistic 3P), FUNAAB Alpha (8.85 weeks, Gompertz 3P and 10.21 weeks, logistic 3P), Fulani (11.45 weeks, Gompertz 4P and 12.22 weeks, logistic 4P) and Shika-Brown (9.59 weeks, Gompertz 3P and 10.85 weeks, logistic 3P). The age at the inflection point at 10 weeks (70 days) in Sasso chicken as observed in Table 4 was lower than the previously reported 74.2–79.8 days in SASSO T44 populations but higher than the 63.7 days in White Cornish population, as reported by Knizetova et al. (1985). The difference between Noiler and the other breeds in the inflection points (age and weight) could be due to the fact that Noiler birds came into the experiment at 42 d of age when compared to the other breeds that were monitored from day old.

For data collected on female birds raised on-station (Table 5), all the computational models (3P and 4P logistic models, 3P and

Table 4. Estimated growth curve parameters of male birds raised on-station from 0 to 20 weeks.

Breed/Model	a	b	c	d	Age and weight at inflection point	AIC	BIC	RMSE	$AdjR^2$
Noiler									
Gompertz 3P	0.15	7.70		2655.67	13;1944.67	89.819	76.804	22.119	0.997
Logistic 3P	0.23	9.54		2463.77	13;1948.67	97.141	84.125	34.954	0.995
Logistic 4P	0.09	8.89	8762.66	3008.00	13;1944.03	102.172	72.569	16.666	0.994
Gompertz 4P	0.09	5.22	4665.65	3032.98	13;1943.34	102.202	72.599	16.697	0.994
Neural network					13;1978.46			4.837	0.995
Kuroiler									
Gompertz 3P	0.17	8.83		2780.35	10;1841.10	122.196	117.121	37.637	0.996
Gompertz 4P	0.18	8.89	34.97	2735.53	10;1844.48	128.630	118.619	38.624	0.994
Logistic 3P	0.31	10.14		2442.10	10;1255.99	130.429	125.354	54.721	0.990
Logistic 4P	0.26	9.92	−157.44	2539.96	10;1839.29	131.732	121.721	44.473	0.989
Neural network					10;1839.14			22.383	0.995
Sasso									
Gompertz 3P	0.16	9.76		3234.25	10;1841.10	121.270	116.195	36.087	0.996
Gompertz 4P	0.17	9.77	39.36	3166.26	10;1844.48	127.171	117.160	36.146	0.992
Logistic 3P	0.30	10.92		2766.72	10;1204.82	130.038	124.963	53.756	0.990
Logistic 4P	0.26	10.80	−151.75	2884.83	10;1251.54	130.222	120.211	41.523	0.990
Neural network					10;1250.91			34.047	0.993
FUNAAB Alpha									
Logistic 3P	0.34	10.21		2021.36	10;1076.42	118.040	112.964	31.158	0.994
Logistic 4P	0.31	10.09	−60.75	2053.46	10;1072.47	120.974	110.963	27.272	0.994
Gompertz 3P	0.19	8.85		2247.64	10;1037.36	120.983	115.908	35.619	0.994
Gompertz 4P	0.21	8.99	53.01	2192.17	10;1044.32	123.863	113.853	31.100	0.992
Neural network					10;1036.72			16.115	0.995
Fulani									
Gompertz 3P	0.13	11.57		1698.40	10;518.22	106.435	101.360	18.386	0.996
Logistic 3P	0.27	12.13		1332.09	10;496.11	111.393	106.318	23.033	0.992
Gompertz 4P	0.14	11.45	17.31	1642.36	10;506.23	112.921	102.910	18.912	0.996
Logistic 4P	0.23	12.22	−61.06	1408.14	10;516.13	113.370	103.359	19.302	0.992
Neural network					10; 523.12			17.933	0.995
Shika-Brown									
Gompertz 3P	0.17	9.59		1823.49	10;756.98	107.869	102.794	19.624	0.998
Gompertz 4P	0.18	9.65	30.33	1780.58	10; 753.56	110.652	100.642	17.059	0.995
Logistic 4P	0.29	10.73	−60.89	1635.98	10;733.29	111.543	101.532	17.764	0.995
Logistic 3P	0.32	10.85		1594.98	10;723.88	112.335	107.264	24.046	0.990
Neural network					10;746.52			9.154	0.998

Notes: AIC: akaike information criterion; BIC: Bayesian information criterion; RMSE: root mean square error; $AdjR^2$: adjusted coefficient of determination; *a* is the maturity index; *b* is the scale parameter; *c*is the asymptotic weight; *d* is the upper asymptote. Non-linear model adapted from JMP 13.2 statistical software

Table 5. Estimated growth curve parameters of female birds raised on-station from 0 to 20 weeks.

Breed/model	a	b	c	d	Age and weight at inflection point	AIC	BIC	RMSE	*AdjR*^{2}
Fulani									
Logistic 4P	0.26	11.35	−38.10	1429.00	10; 452.42	90.350	80.340	6.779	0.995
Logistic 3P	0.28	11.38		1109.22	10; 446.99	95.497	90.422	11.183	0.992
Gompertz 3P	0.14	10.46		1347.86	10; 463.54	99.351	94.276	13.324	0.989
Gompertz 4P	0.16	10.41	24.80	1292.41	10; 461.67	102.561	92.550	11.809	0.988
Neural network					10; 469.75			5.933	0.992
FUNAAB Alpha									
Logistic 3P	0.40	10.41		2780.35	10;1030.22	121.831	116.756	37.019	0.994
Gompertz 3P	0.20	9.07		2735.53	10;1070.99	125.555	120.480	43.846	0.990
Logistic 4P	0.30	10.32	−49.12	2247.55	10;1037.22	126.763	116.753	35.482	0.990
Gompertz 4P	0.22	9.21	59.16	2392.08	10;1067.04	128.188	118.177	37.856	0.989
Neural network					10;1084.91			38.829	0.990
Sasso									
Gompertz 3P	0.14	10.89		3856.63	10;1240.85	127.704	122.629	48.346	0.997
Gompertz 4P	0.14	10.88	7.06	3838.13	10;1240.36	135.016	125.006	51.633	0.992
Logistic 3P	0.28	11.76		3155.02	10;1192.88	138.815	133.740	80.110	0.988
Logistic 4P	0.23	11.82	−232.47	3412.27	10;1221.52	139.646	129.635	63.726	0.987
Neural network					10;1261.09			38.913	0.997
Kuroiler									
Gompertz 3P	0.14	10.40		3725.38	10;1292.28	119.769	114.694	33.706	0.995
Gompertz 4P	0.14	10.43	−23.13	3777.74	10;1293.34	126.740	116.729	35.444	0.991
Logistic 4P	0.21	11.38	−300.25	3385.91	10;1276.43	132.982	122.972	47.074	0.990
Logistic 3P	0.28	11.41		3090.09	10;1246.74	137.304	132.228	74.792	0.985
Neural network					10;1290.89			17.773	0.996
Shika-Brown									
Gompertz 3P	0.17	10.09		2088.27	10; 756.01	115.702	110.627	28.016	0.998
Logistic 3P	0.32	11.27		1803.37	10; 722.05	116.621	111.546	29.213	0.998
Logistic 4P	0.29	11.19	−58.62	1847.41	10; 732.26	118.844	108.833	24.756	0.998
Gompertz 4P	0.18	10.13	32.93	2034.90	10; 752.68	120.354	110.343	26.514	0.995
Neural network					10; 712.52			7.287	0.998
Noiler									
Gompertz 3P	0.18	7.97		2917.67	13;1955.35	105.461	92.445	58.794	0.992
Logistic 3P	0.27	9.66	30.33	2742.17	13;1959.03	108.221	95.206	69.867	0.990
Logistic 4P	0.13	0.44	−5131.7	3139.89	13;1947.59	122.384	92.781	58.948	0.989
Gompertz 4P	0.12	0.22	−3231.4	3204.77	13;1946.85	122.442	92.839	59.162	0.989
Neural network					13;1916.49			49.327	0.990

Notes: AIC: akaike information criterion; BIC: Bayesian information criterion; RMSE: root mean square error; AdjR^2: adjusted coefficient of determination; *a*is the maturity index; *b*is the scale parameter; *c*is the asymptotic weight; *d* is the upper asymptote. Non-linear model adapted from JMP 13.2 statistical software.

4P Gompertz and Neural network) fitted the data satisfactorily. It is known that the model with the highest *AdjR*^{2} and the lowest AIC value better explains the change in body weight (Keskin and Dag 2006; Sahin et al. 2014). Neural network had the best accuracy of reconstructing the body weight across the TADP chickens with the highest *AdjR*^{2} (0.992–0.998) and the lowest

Table 6. Estimated growth curve parameters of male birds raised on-farm from 6 to 18 weeks.

Breed/Model	*a*	*b*	*c*	Age and weight at inflection point	BIC	RMSE	*AdjR*^{2}
Fulani							
Logistic 3P	0.17	10.78	1016.74	12; 563.64	36.204	22.344	0.995
Gompertz 3P	0.09	9.75	1265.43	12; 562.83	37.623	26.682	0.994
Neural network				12; 642.12		0.278	0.997
FUNAAB Alpha							
Logistic 3P	0.17	11.19	1428.31	12; 764.51	24.981	5.494	0.992
Gompertz 3P	0.09	10.17	1779.54	12; 765.02	7.205	0.595	0.997
Neural network				12; 751.98		46.771	0.954
Kuroiler							
Logistic 3P	0.12	14.32	2156.09	12; 928.19	34.724	18.572	0.997
Gompertz 3P	0.05	17.47	3494.67	12; 923.87	36.024	21.847	0.996
Neural network				12; 938.78		12.086	0.991
Noiler							
Logistic 3P	0.13	8.96	1756.81	12; 1044.40	42.410	48.537	0.982
Gompertz 3P	0.07	7.04	2105.78	12; 1043.13	42.846	51.258	0.980
Neural network				12; 1028.25		10.442	0.982
Sasso							
Logistic 3P	0.12	15.15	2216.87	12; 895.49	34.093	17.161	0.997
Gompertz 3P	0.05	19.82	3886.69	12; 895.26	35.463	20.368	0.994
Neural network				12; 819.29		0.321	0.997
Shika-Brown							
Logistic 3P	0.14	15.92	1516.39	12; 552.75	24.871	5.419	0.996
Gompertz 3P	0.05	21.31	2867.28	12; 553.59	18.237	2.364	0.998
Neural network				12; 481.77		47.673	0.928

Notes: BIC: Bayesian information criterion; RMSE: root mean square error; *AdjR*^{2}: Adjusted coefficient of determination; *a*is the maturity index; *b* is the scale parameter; *c*is the asymptotic weight. Non-linear model adapted from JMP 13.2 statistical software

Table 7. Estimated growth curve parameters of female birds raised on-farm from 6 to 18 weeks.

Breed/Model	*a*	*b*	*c*	Age and weight at inflection point	BIC	RMSE	*AdjR²*
Fulani							
Logistic 3P	0.09	7.18	1192.26	12; 723.04	25.384	5.778	0.997
Gompertz 3P	0.05	3.85	1373.79	12; 723.15	24.373	5.092	0.998
Neural network				12; 727.91		2.847e-9	0.998
FUNAAB Alpha							
Logistic 3P	0.09	14.59	1846.63	12; 811.97	47.805	95.274	0.933
Gompertz 3P	0.08	5.80	1520.89	12; 829.51	49.611	119.400	0.894
Neural network				12; 696.01		6.0297e-6	0.990
Kuroiler							
Logistic 3P	0.12	11.02	1875.97	12; 992.40	31.062	11.749	0.995
Gompertz 3P	0.06	10.11	2417.80	12; 992.14	32.653	14.334	0.991
Neural network				12; 925.09		5.876e-5	0.996
Noiler							
Logistic 3P	0.10	8.43	1708.59	12; 1007.80	39.106	32.116	0.992
Gompertz 3P	0.06	6.16	2055.12	12; 1007.11	39.457	33.559	0.991
Neural network				12; 1027.10		3.276e-8	0.997
Sasso							
Logistic 3P	0.09	16.91	2360.79	12; 924.74	36.244	22.456	0.995
Gompertz 3P	0.03	25.67	4533.37	12; 924.24	36.697	23.764	0.995
Neural network				12; 969.06		7.079e-7	0.996
Shika-Brown							
Logistic 3P	0.09	9.89	1253.06	12; 688.54	21.555972	3.580	0.997
Gompertz 3P	0.05	8.11	1563.17	12; 688.47	23.320516	4.464	0.994
Neural network				12; 687.62		37.579	0.897

Notes: BIC: Bayesian information criterion; RMSE: root mean square error; $AdjR^2$ is the Adjusted coefficient of determination; *a* is the maturity index; *b* is the scale parameter; *c* is the asymptotic weight. Non-linear model adapted from JMP 13.2 statistical software.

RMSE (5.993–49.327). The $AdjR^2$ values obtained in this study for all the models are greater than 0.98 and higher than the values reported by Cetin et al. (2007) and Yakubu and Madaki (2017) for linear, quadratic, Gompertz and neural network. The age at the inflection point of 13 weeks in Noiler was higher than the 10 weeks for Fulani, Sasso, Shika-Brown, FUNAAB Alpha and Kuroiler estimated in female birds raised on-station from 0 to –20 weeks by the prediction profiler (Table 5).

Table 8. Estimated growth curve parameters by breed of TADP chickens raised on-station and on-farm.

Breed/Model	*a*	*b*	*b*	*d*	Age and weight at inflection point	AIC	BIC	RMSE	*AdjR²*
Fulani									
Gompertz 3P	0.12	12.51		2008.60	10;518.22	106.55	101.47	18.48	0.996
Logistic 3P	0.12	9.54		2463.77	10;496.11	108.94	103.87	20.61	0.993
Logistic 4P	0.23	12.86	−58.87	1597.92	10;506.23	109.19	99.18	15.96	0.990
Gompertz 4P	0.13	12.31	18.21	1932.78	10;516.13	112.96	102.95	18.94	0.990
Neural network					10;502.72			9.93	0.994
FUNAAB Alpha									
Logistic 3P	0.35	10.42		2235.92	10;1037.36	119.47	114.40	33.26	0.994
Logistic 4P	0.32	10.33	−49.85	2262.82	10;1044.34	124.03	114.02	31.34	0.989
Gompertz 3P	0.19	9.09		2489.17	10;1076.42	126.40	121.33	45.57	0.987
Gompertz 4P	0.21	9.22	61.38	2423.22	10;1839.29	129.76	119.75	40.66	0.988
Neural network					10;1024.32			26.09	0.992
Kuroiler									
Gompertz 3P	0.14	10.49		3790.20	10;1300.39	118.39	113.32	31.67	0.998
Gompertz 4P	0.13	10.55	−45.65	3897.82	10;1302.31	124.38	114.37	31.84	0.993
Logistic 4P	0.19	11.45	−339.68	3461.48	10;1204.82	129.70	119.69	40.56	0.993
Logistic 3P	0.27	11.46		3115.45	10;1255.99	136.85	131.78	73.29	0.992
Neural network					10;1333.33			40.74	0.998
Noiler									
Gompertz 3P	0.16	7.95		3005.15	10;1076.42	101.24	88.22	45.17	0.996
Logistic 3P	0.25	9.71		2792.96	10;1948.67	102.29	89.27	48.23	0.993
Logistic 4P	0.19	7.62	−852.21	2942.83	10;1944.03	119.30	89.70	48.63	0.996
Gompertz 4P	0.16	7.40	−178.53	3045.92	13;1943.34	119.84	90.24	50.30	0.996
Neural network					13;1928.13			26.23	0.996
Sasso									
Gompertz 3P	0.12	12.51		2008.60	10;518.22	106.55	101.47	18.48	0.995
Logistic 3P	0.26	12.71		1511.42	10;496.10	108.94	103.87	20.61	0.992
Logistic 4P	0.23	12.86	−58.86	1597.92	10;506.23	109.19	99.18	15.96	0.989
Gompertz 4P	0.13	12.31	18.21	1932.78	10;516.13	112.96	102.95	18.94	0.988
Neural network					10; 507.13			14.83	0.996
Shika-Brown									
Gompertz 3P	0.37	10.01		2282.66	10;1618.32	103.44	91.65	32.14	0.998
Logistic 3P	0.22	11.22		1942.00	10;1426.20	104.67	93.89	25.07	0.995
Logistic 4P	0.27	10.41	−28.33	1682.12	10;1606.45	122.30	94.32	11.22	0.994
Gompertz 4P	0.38	12.56	6.49	1876.26	10;1316.13	112.96	99.14	29.24	0.978
Neural network					10;1211.19			11.81	0.999

Notes: AIC: akaike information criterion; BIC: Bayesian information criterion; RMSE: root mean square error; AdjR^2 is the adjusted coefficient of determination; *a* is the maturity index; *b* is the scale parameter; *c* is the asymptotic weight; *d* is the upper asymptote. Non-linear model adapted from JMP 13.2 statistical software.

For the data collected from male birds raised on-farm from 6 to 18 weeks (Table 6), the 4P models (logistic 4P and Gompertz 4P) had poor iterations and failed to converge in modelling the growth curves due to optimization problem which made the parameters not estimable. Our results show huge disagreement between the observed and predicted male data for 4P models. The logistic 3P had the highest $AdjR^2$ in Fulani, Kuroiler, Noiler and Sasso. This implies that logistic 3P fitted the liveweight data more accurately.

The age at inflection point at 12 weeks (84 days of age) of male birds raised on-farm from 6 to 18 weeks in this study was higher than the results obtained in local genotypes of slow-growing broilers (44.00 and 49.62 days of age) using the Gompertz model (N'dri et al. 2006; Dourado et al. 2009). The age at the inflection point in the present study was similar to those reported by Yapi et al. (2011) for indigenous local ecotypes (savannah and forest) and that of slow-growing broilers obtained by Narinç et al. (2010) in Hubbard. Logistic 3P had the best maturity index in TADP chickens.

Estimated growth curve parameters of female birds raised on-farm from 6 to 18 weeks are presented in Table 7. Logistic 3P had higher scale parameters for Fulani (7.18 weeks), FUNAAB Alpha (14.59 weeks), Kuroiler (11.02 weeks), Noiler (8.43 weeks) and Shika-Brown (9.89 weeks) which are similar to estimates reported by Yang et al. (2006) in Jinghai (Chinese) yellow chickens.

The maturity index of 0.03–0.12 for female birds raised on-farm from 6 to 18 weeks in this study was close to the 0.137 reported for an Italian nondescript chicken breed from 2 to –24 weeks of age (Darmani et al. 2010) but higher than the values reported by Ait and Moula (2013) for chickens of Kabyle in Algeria (0.0260 and 0.0294 g d^{-1}), and by Yapi et al. (2011) for indigenous local chickens in Cote d'Ivoire (0.0189 vs. 0.0205 g d^{-1}).

Estimated growth curve parameters by breed in TADP chickens raised on-station and on-farm are presented in Table 8 and Figure 1. We advocated for the increase in power of prediction by pooling the male and female record to increase the sample size despite the fact that sexual dimorphism was observed in this study. The highest adjusted coefficient of determination (0.999) was recorded in ANN model in Shika-Brown in the pooled data which was higher than when the sex was considered singularly. The utilization of the ANN statistical methodology may provide livestock managers another tool in the evaluation of data to assist in the development of appropriate TADP chicken management plans for genetic improvement strategies. Fulani had the least AIC value across the models (90.35–102.56), followed by Noiler (105.46–122.44) and Shika-Brown (108.83–111.54). Gompertz 3P had the best goodness of fit in Sasso, Kuroiler, Shika-Brown and Noiler, respectively. Gompertz model had a lower maturity index in all the breeds than logistic models. Kuroiler had the heaviest upper asymptotic weight (3115.45–3897.82 g) which was higher than the 675.3–886 gm for the Kabyle traditional chickens reported by Ait and Moula (2013), and the 1501.2–2219.5 gm for the local chicken in Cote d'Ivoire, as obtained by Yapi et al. (2011). The differences could be attributed to the fact that Kuroiler is an improved Indian local chicken, while the Kabyle and Ivorian local chickens are unimproved. In this study, the improved TADP chickens had an earlier scale parameter than the unimproved Fulani chickens. This is in agreement with the report of Mignon and Beaumont (2000) that animals selected for heavier body weight arrive at the age at the inflection point and scale parameters earlier.

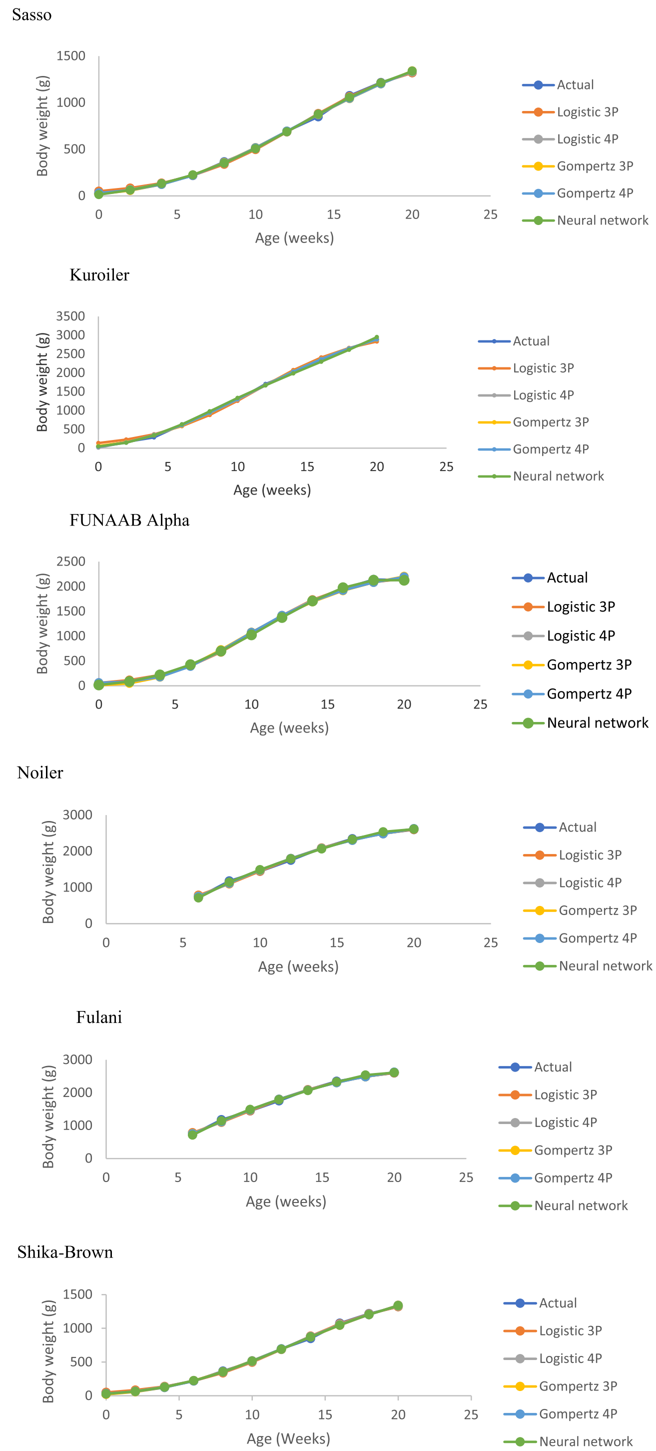

Figure 1. Growth curve parameters of the TADP breeds.

Conclusion

From the results above, it can be concluded that non-linear models and neural network model yielded good fit with the age-weight data of TADP chickens on-station and on-farm. However, these results validate the fact that neural network models can compete with non-linear models for modelling of the body weight data at different ages and thereby expanding the statistical tool kit available to analyse data and make predictions in TADP chickens. The stability of biological parameters of non-linear offers an advantage for effective planning of feed resources for optimal utilization and breeding improvement strategy in TADP chickens.

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