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Comprehensive growth modelling of Adana dewlap pigeons' chicks using adaptive Kalman filter techniques

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Abstract

Adana Dewlap pigeons are a unique breed native to the Adana region of Turkey, recognized for their distinctive flight characteristics. The current study investigates the growth dynamics of these pigeons using both traditional and advanced modeling techniques, aiming to identify the most accurate approach. Due to their limited reproductive cycle (typically two or three clutches per year), only a few offspring can be reared annually from a single pair, and many hatchlings do not reach sexual maturity. A dataset comprising 43-day body weight measurements from 88 pigeons collected over seven years was used. The average daily weight was modeled using well-established growth functions, including the Richards, Logistic, and Gompertz models. MATLAB scripts were developed for parameter estimation, and the reliability of model predictions was evaluated using metrics such as Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and R^2. In addition to static models, this study emphasizes the importance of capturing the temporal dynamics of growth in avian species like the Adana Dewlap pigeon. The Adaptive Kalman Filter (AKF) was employed to decompose the growth process into position, velocity, and acceleration for a more detailed analysis. The velocity curve shows a rapid increase in weight gain during the first two weeks, consistent with a critical post-hatch developmental phase. This is followed by gradual deceleration, suggesting that the pigeons reach a physiological threshold at which weight gain slows due to metabolic adaptation or genetic constraints. Acceleration analysis further substantiates this trend, with positive values during early development and negative values during later stages, characteristic of the asymptotic phase of sigmoidal growth curves, as described by the Logistic, Gompertz, and Richards models. These results demonstrate that AKF not only fits observed data accurately but also reveals latent transitions in growth behavior, offering a robust tool for real-time monitoring and analysis in biological development studies.

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Introduction

Pigeons have historically played a significant role in human civilization, symbolizing peace, communication, and companionship. Domesticated pigeons, which descend from the wild rock pigeon (Columba livia), display remarkable phenotypic diversity as a result of centuries of selective breeding (1-3). Among these, the Adana Dewlap pigeon, selectively bred in the Adana region of southern Turkey, is particularly notable for its distinct skeletal structure, prominent dewlap, and characteristic flight behavior. Despite their cultural and genetic significance, the developmental biology and growth patterns of this breed remain largely underexplored in the scientific literature. Accurately modeling avian growth is essential for biological research, conservation efforts, and the optimization of breeding strategies. Growth models provide valuable insights into developmental phases, physiological constraints, and energy allocation mechanisms across the life span. Classical mathematical models-such as the Gompertz, Logistic, and Richards functions-have been widely employed to describe the sigmoidal growth trajectories of various species.

While these static models effectively capture overall growth trends, they often fall short in accounting for local variations, measurement noise, and environmental or physiological fluctuations commonly observed in real biological systems. To address these limitations, the present study combines both static and dynamic modeling approaches to analyze the growth dynamics of Adana Dewlap pigeons. The empirical analysis is based on a unique longitudinal dataset comprising 43-day body weight measurements from 88 pigeon chicks collected over seven years. Initially, traditional growth models such as the Logistic, Richards, and Gompertz functions were applied and evaluated using statistical performance indicators, including Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). Beyond static curve-fitting, the study introduces a dynamic state-space framework utilizing the Kalman Filter (KF) and its adaptive variant, the Adaptive Kalman Filter (AKF). While the standard KF is suitable for estimating latent variables, such as growth velocity and acceleration from noisy weight data, the AKF enhances adaptability by dynamically updating the process noise covariance. This allows the model to respond effectively to abrupt changes in growth behavior, such as those caused by feeding variations or metabolic adaptation.

The AKF approach decomposes the growth trajectory into three interpretable components: position (body weight), velocity (rate of weight gain), and acceleration (rate of change in gain). This decomposition provides a deeper and more dynamic understanding of the temporal evolution of growth under biologically uncertain conditions. The results demonstrate that while traditional models effectively characterize the overall sigmoidal growth curve, they are limited in detecting short-term fluctuations and transitional phases. In contrast, the AKF captures early-stage acceleration and late-stage deceleration with greater fidelity, reflecting the underlying biological processes. By integrating classical growth functions with adaptive filtering techniques, this study offers a robust, real-time, and flexible framework for modeling avian growth. The proposed approach has broad applicability in animal science, precision poultry farming, and veterinary diagnostics, where dynamic growth monitoring and anomaly detection are increasingly essential. The growth process in animals is a complex biological phenomenon influenced by both genetic structure and environmental conditions. Quantitative modeling of this process is of critical importance in poultry production for determining growth potential, guiding breeding strategies, and optimizing feeding programs.

In this context, sigmoidal mathematical models are commonly used to represent growth curves. Among these, the Gompertz, Logistic, and Richards functions are widely applied. The mathematical modeling of avian growth has become an essential field in poultry science due to its implications for genetic selection, feeding strategies, and production efficiency. Numerous nonlinear models, such as the Gompertz, Logistic, and Richards models, have been extensively used to describe biological growth curves. Narinç *et al.* (4) emphasized the suitability of Gompertz and Richards models for poultry growth. They highlighted the biological flexibility of the latter. Similarly, Darmani Kuhi *et al.* (5) reviewed a wide range of growth models, favoring flexible four-parameter models such as Richards and López for their superior performance across various experimental conditions.

Extending this literature to underrepresented avian types, Özbek (6-8) conducted a series of studies focusing specifically on Adana dewlap pigeons, a regionally unique breed from southern Turkey. In one study, nine nonlinear models were systematically compared using a 43-day average weight dataset from 68 pigeons. The Richards model yielded the best fit based on MSE, MAPE, and R^2. In a subsequent study (8), the sample size was increased to 88 pigeons, and the same outcome was again observed. Beyond static curve fitting, Özbek (8) also applied a Discrete-Time Stochastic Gompertz Model (DTSGM), wherein the time-varying parameter was estimated using an Adaptive Kalman Filter (AKF). This approach, modeled as a time-varying AR(1) process, allowed real-time parameter estimation and exhibited excellent predictive accuracy with low error metrics ($MSE \approx 270$; $R^2 \approx 0.98$; $MAPE \approx 2.3\%$). Kalman filtering's recursive structure also allowed adaptive modeling even under data non-stationarity, as confirmed through Augmented Dickey-Fuller tests. Together, these studies fill a significant gap in the literature by systematically comparing classical nonlinear models and introducing dynamic time-series modeling for species of pigeon growth rarely studied in this context. The results consistently support the Richards function for static analysis and the DTSGM + AKF framework for dynamic growth modeling. The observed variation in clutch intervals across seasons is closely linked to environmental factors. During fall and winter, the interval between clutches is approximately 45 days.

In contrast, in spring and early summer, it shortens to 30–32 days. This seasonal difference can be attributed to more favorable environmental conditions in spring and summer, including longer daylight duration, milder temperatures, and improved food availability. These factors collectively enhance the reproductive efficiency of pigeons and reduce the recovery time between clutches. Therefore, spring and early summer represent the peak of the broodiness season for most pigeon breeds (9-10).

Pigeon chicks are altricial, meaning they hatch in a highly undeveloped state and are entirely dependent on parental care. Two factors are critical for their survival and growth during the early post-hatching period: (i) Nutrition, primarily provided in the form of crop milk-a nutrient-rich secretion produced by both parents, though predominantly by the mother, and (ii) Thermoregulation, which is maintained through the mother's brooding behavior since the chicks cannot regulate their body temperature independently at this stage. Maternal body weight serves as an indirect indicator of nutritional status and crop milk production capacity. A well-nourished mother with sufficient energy reserves is better equipped to meet both the demands of intensive feeding and thermoregulation. Thus, maternal weight and the efficiency of the nutritional system are essential determinants of early chick development and survival in pigeons (11-13).

Materials and methods

Gompertz Model

In this section, the most commonly used growth models in the literature are explained (14-16).

$W(t) = A.\exp(-\exp(B-Kt))$

Where $W(t)$: Body weight at time t, A: Asymptotic maximum weight, B: Displacement along the time axis, K: Growth rate constant.

Logistic Model

$$W(t) = \frac{A}{1+\exp(B-Kt)}$$

Where: A: Asymptotic maximum weight. B: Displacement. K: Growth rate constant.

Richards Model

$$W(t) = A.(1+v.\exp(-K(t-t_0)))^{-1/v}$$

Where: A: Asymptotic maximum weight. K: Growth rate constant. t_0: Inflection point. v: Shape parameter (flexibility).

State-space model for pigeon growth

Linear discrete-time stochastic state-space models were developed in the 1960s for applications such as tracking and controlling the position of satellites, guided missiles, spacecraft, and maneuverable targets. In addition, state-space modeling has found widespread use for modeling physical, physiological, and economic processes (17-20). The estimation of the state vector in a linear discrete-time stochastic state-space model was introduced by Kalman (21). The Kalman Filter (KF) is essentially a recursive solution to the least-squares estimation problem (22-24). There is a substantial body of literature on the Kalman filter, including its derivation, theoretical properties, and diverse applications (25-30). The general form of a discrete-time linear state-space model consists of two equations:

State Equation: $x_{k+1} = A_k x_k + w_k$

Observation Equation: $y_k = H_k x_k + v_k$

Where: $x_k \in \Re^n$ is the state vector (true unobserved states). $y_k \in \Re^m$ is the observation vector (measured outputs). A_k is the state transition matrix. H_k is the observation matrix. $w_k \in \Re^n$ is process noise, assumed to be Gaussian with covariance Q. $v_k \in \Re^m$ is measurement noise, assumed to be Gaussian with covariance R.

Growth, velocity, and acceleration definitions

The growth of pigeons is represented by the weight function $W(t)$. The first derivative of the weight with respect to time means the growth velocity $v(t)$:

$$v(t) = \frac{dW(t)}{dt}$$

The second derivative defines the growth acceleration $a(t)$:

$$v(t) = \frac{d^2W(t)}{dt^2}$$

In this study, the state vector x_k is constructed from three quantities: weight, velocity, and acceleration. The state vector is explicitly defined as:

$$x_k = \begin{bmatrix} W_k \\ v_k \\ a_k \end{bmatrix}$$

Where W_k : Represents the body weight at time step k, v_k : Represents the growth velocity (the first derivative of weight), a_k : Represents the growth acceleration (the second derivative of weight).

For the pigeon growth modeling application: $x_k = \begin{bmatrix} W_k \\ v_k \\ a_k \end{bmatrix}$

Where: W_k: Estimated body weight at time k. v_k: Estimated velocity (first derivative of weight). a_k: Estimated acceleration (second derivative of weight).

The system matrices are defined as: $A_k = \begin{bmatrix} 1 & \Delta t & 0.5\Delta t^2 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix}$

$H_k = [1, 0, 0]$

Where Δt = 1 day. The Kalman filter, based on initial values of $\hat{x}_0^+$ and P_0^+, is defined by the following equations:

$$\hat{x}_k^- = A_{k-1}\hat{x}_{k-1}^+, \; P_k^- = \lambda_k(A_{k-1}P_{k-1}^+A_{k-1}^T + Q_{k-1})$$

$$n_k = y_k - H_k\hat{x}_k^-, \; P_{n_k} = H_k P_k^- H_k^T + R_k$$

$$K_k = P_k^- H_k^T (P_{n_k})^{-1}, \; \hat{x}_k^+ = \hat{x}_k^- + K_k n_k, \; P_k^+ = (I - K_k H_k)P_k^-$$

K_k, known as the Kalman Gain Matrix (25-28). Here n_k, represents the innovation vector with the covariance matrix P_{n_k}.

Results

The dataset used in this study consists of growth measurements collected from Adana Dewlap pigeons. The weights obtained from the measurements are given in Table 1. This breed is characterized by rapid early-stage growth, medium body size, and a robust skeletal structure. Their consistent genetic background and controlled breeding environment provide a reliable foundation for quantitative growth modeling. These attributes make Adana pigeons an ideal subject for evaluating the performance of dynamic estimation techniques, such as the Kalman Filter (KF) and Adaptive Kalman Filter (AKF).

Table 1: Weights obtained from measurements

Day	Weight	Day	Weight
1	14	22	375
2	20	23	406
3	30	24	415
4	45	25	408
5	63	26	425
6	85	27	421
7	106	28	414
8	134	29	428
9	167	30	431
10	189	31	432
11	224	32	437
12	237	33	431
13	269	34	416
14	294	35	428
15	295	36	420
16	295	37	419
17	327	38	428
18	344	39	421
19	343	40	424
20	379	41	424
21	378	42	429
		43	430

To the best of our knowledge, this study is the first to simultaneously model the weight, velocity, and acceleration dynamics of Adana pigeons using both KF and AKF. Previous research has primarily focused on weight estimation alone, without incorporating higher-order derivatives or dynamic modeling. In this study, real-world pigeon growth data were used for analysis. Both the Kalman Filter and its adaptive counterpart were applied to the dataset. Results show that the AKF outperformed the standard KF, yielding lower Root Mean Squared Error (RMSE) values, demonstrating its superior ability to capture the underlying growth dynamics under real conditions (Table 2).

As shown in Table 3 and Figures 1-3, the Richards model provided the best fit among the traditional static models, closely followed by the Gompertz model. Both models captured the sigmoidal nature of growth, but Richards exhibited superior accuracy across all metrics. The Logistic model showed higher MSE and Mean Absolute Percentage Error (MAPE), indicating lower predictive performance. MSE R^2 and MAPE equations are given in the appendix.

Table 2: Static Growth Model Comparisons

Model	MSE	R^2	MAPE (%)
Richards	77.18	0.9957	2.28
Gompertz	77.41	0.9957	2.31
Logistic	133.32	0.9925	7.99

Table 3: Adaptive Kalman Filter Performance

Model	MSE	R^2	MAPE (%)
AKF	41.84	0.9977	2.19

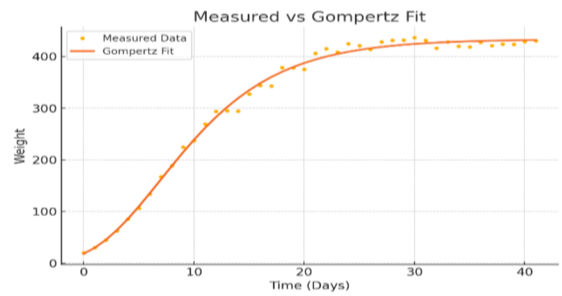

Figure 1: Measured vs Gompertz Fit.

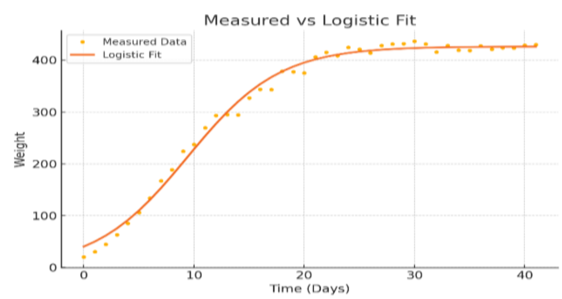

Figure 2: Measured vs Logistic Fit.

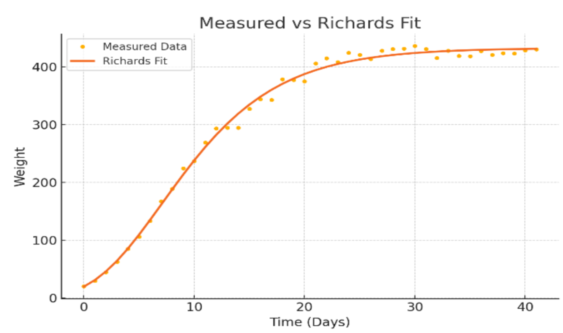

Figure 3: Measured vs Richards Fit.

According to table 2 and figures 4 and 5, the AKF approach significantly outperformed all static models. The reduction in MSE and increase in R^2 and MAPE underscore AKF's ability to dynamically adjust to biological variability in growth. In biological systems, particularly in avian species like Adana Dewlap pigeons, understanding not only the final body weight but also the Dynamics of how that weight changes over time is essential. The Kalman filtering approach, especially in its adaptive form, allows us to dissect these changes into measurable, interpretable trends that offer valuable insight into growth patterns. The velocity plot highlights that growth is not constant: there is a noticeable increase in weight gain during the first two weeks. This corresponds to a critical post-hatch developmental phase, during which nutritional intake and tissue development are at their peak. As time progresses, the velocity flattens, suggesting that the pigeons have reached a physiological threshold at which additional weight gain slows due to metabolic adaptation or the approach of genetic potential.

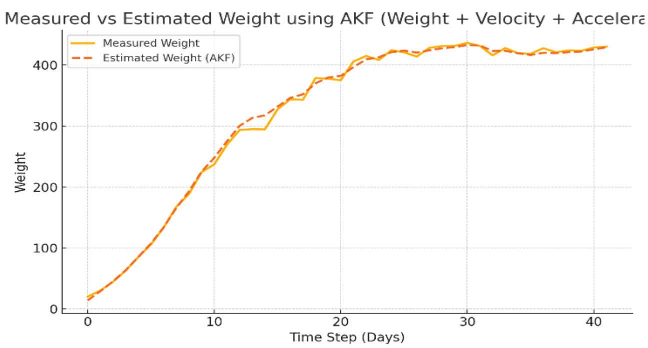

Figure 4: Measured vs Estimated Weight using AKF (Weight + Velocity Acceleration).

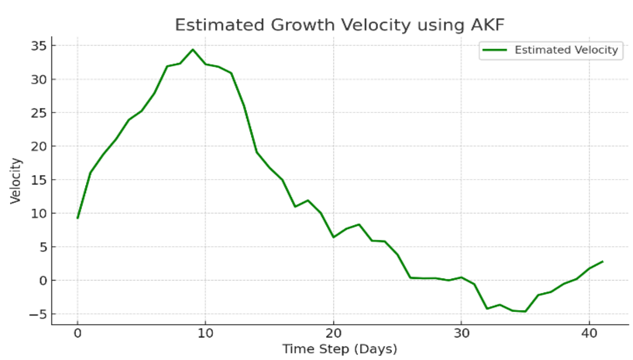

Figure 5: Estimated Growth Velocity using AKF.

Discussion

Recent veterinary studies have demonstrated the effectiveness of molecular modeling approaches for pathogen identification in livestock infections, particularly Theileria species (29). Integrating bacterial resistance data, such as those related to Escherichia coli prevalence in poultry environments, enhances the robustness of biological system modeling (31).

The acceleration plot is particularly informative. The early-stage positive acceleration reflects a healthy, natural growth trajectory. However, the latter negative acceleration indicates the beginning of the asymptotic phase of the sigmoidal growth curve, commonly modeled by Gompertz or Richards functions. This consistency suggests that the AKF not only fits the data but can reveal latent growth transitions more explicitly. Similar to tissue reconstruction in canine urinary models, the adaptive dynamics observed in pigeon growth may reflect underlying regenerative physiology (32).

The impact of probiotics on microbial balance and nutrient absorption has been confirmed in avian models, supporting the observed modulation of growth dynamics (30). Herbal supplementation in poultry, such as in quail growth and egg quality optimization, has shown significant physiological effects that parallel those observed in this study (33). Recent findings on the role of postbiotics in shaping the gut microbiota and improving nutrient digestibility provide further context for interpreting acceleration in growth (34).

The Richards model yielded the best overall fit among traditional static models, corroborating its known flexibility and suitability for biological growth phenomena. However, its inability to accommodate real-time fluctuations limits its ability to accurately model biological systems under dynamic conditions. The Adaptive Kalman Filter (AKF) emerged as a more powerful tool by dynamically adjusting its internal parameters in response to real-time measurement innovations. Unlike static models with fixed structures, AKF accommodates time-varying changes, thus delivering more accurate growth predictions. The observed decrease in MSE and increase in R^2 validate the AKF's enhanced performance. Figures 4 and 5 further highlight the AKF's ability to dynamically track the growth and velocity of Adana dewlap pigeons. While static models like Richards capture overall growth trends, AKF captures transient dynamics and rapid changes, which are crucial in real-world biological monitoring applications.

Furthermore, the incorporation of the state-space modeling framework signifies a methodological advancement not previously applied in pigeon growth studies. By capturing latent dynamics, such as velocity and acceleration, AKF enables more robust decision-making and early anomaly detection in the growth process. These findings suggest that AKF is highly suitable not only for pigeon growth modeling but also for broader applications in precision poultry farming, biological system analysis, and adaptive monitoring, where dynamic variability plays a crucial role. When the models were compared using MSE, MAPE, and R2, the new model we proposed performed better.

Conclusion

This study demonstrates the applicability of Adaptive Kalman Filtering in modeling the multidimensional dynamics of pigeon growth. By decomposing the process into position, velocity, and acceleration, we obtain a comprehensive understanding of both the magnitude and nature of change. Such a layered view is crucial for applications in animal science, breeding optimization, and health monitoring in poultry production systems. This study compared static growth models with an Adaptive Kalman Filter (AKF) approach for modeling the growth dynamics of Adana dewlap pigeons. While the Richards model was the best static option, AKF demonstrated superior performance by accommodating real-time variability and dynamic state estimation. This approach is not only applicable to pigeons but also to broader animal growth modeling scenarios where adaptation to time-varying conditions is essential. The integration of a state-space model with the innovation-driven adjustment mechanism of the AKF yielded a modeling strategy that captures biological growth dynamics with high fidelity. This is particularly relevant for applications requiring continuous monitoring and dynamic control, such as livestock management and veterinary diagnostics. Future research should explore integrating AKF with nonlinear estimation techniques, ensemble filtering approaches, or machine learning methods to further enhance its predictive capabilities. Additionally, applying AKF frameworks to broader biological datasets across multiple species could generalize the findings and strengthen adaptive growth modeling. The estimated velocity (first derivative of position) represents the daily weight gain of the pigeons. It is observed that velocity increases significantly during the initial growth phase, reflecting the rapid development of young pigeons. Around the mid-growth period, the velocity tends to stabilize, indicating that the birds are approaching their growth plateau. In the final phase, the velocity gradually decreases, a typical behavior as the animal reaches its genetically determined size limit. Similarly, the estimated acceleration (the second derivative of position) provides insight into dynamic changes in growth rate. Positive acceleration during early growth days suggests increasing velocity, meaning the pigeons are not only gaining weight but gaining it faster. As the growth stabilizes, the acceleration approaches zero. In later stages, negative acceleration values indicate deceleration in growth, signaling that the pigeons have entered the saturation phase of their growth curve. These patterns are consistent with biological sigmoidal growth behaviors and validate the use of the adaptive Kalman filter for accurately modeling both growth dynamics and their derivatives in avian species.

Conflict of interest

There is no conflict of interest.

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النمذوج الشامل لنمو صغار حمام الأضنة المذلَّف باستخدام تقنيات مرشح كالمان التكيفي

ليفنت أوزبك

قسم الإحصاء، كلية العلوم، جامعة أنقرة، أنقرة، تركيا

الخلاصة

حمام الأضنة المذلَّف هو سلالة فريدة من نوعها موطنها منطقة أضنة في تركيا، وهي معروفة بخصائص طيرانها المميزة. تدرس الدراسة الحالية ديناميكيات نمو هذه الحمام باستخدام تقنيات النمذجة التقليدية والمتقدمة، بهدف تحديد النهج الأكثر دقة. نظرًا لدورتها الإنجابية المحدودة (عادةً براثنتان أو ثلاث براثن سنويًا)، لا يمكن تربية سوى عدد قليل من النسل سنويًا من زوج واحد، والعديد من الصغار لا يصلون إلى مرحلة النضج الجنسي. تم استخدام مجموعة بيانات تشتمل على قياسات وزن الجسم لمدة ٤٣ يومًا من ٨٨ حمامة تم جمعها على مدى سبع سنوات. تمت نمذجة متوسط الوزن اليومي باستخدام وظائف النمو الراسخة، بما في ذلك نماذج ريتشاردز واللوجستيك وجومبرتز. تم تطوير نصوص MATLAB لتقدير المعلمات، وتم تقييم موثوقية تنبؤات النموذج باستخدام مقاييس مثل متوسط الخطأ التربيعي (MSE)، ومتوسط الخطأ المطلق النسبي (MAPE)، وR^2. بالإضافة إلى النماذج الثابتة، تؤكد هذه الدراسة على أهمية التقاط الديناميكيات الزمنية للنمو في أنواع الطيور مثل حمام الأضنة المذلَّف. تم استخدام مرشح كالمان التكيفي (AKF) لتحليل عملية النمو إلى الموضع والسرعة والتسارع للحصول على تحليل أكثر تفصيلاً. يُظهر منحنى السرعة زيادة سريعة في زيادة الوزن خلال الأسبوعين الأولين، بما يتوافق مع مرحلة النمو الحرجة بعد الفقس. ويتبع ذلك تباطؤ تدريجي، مما يشير إلى أن الحمام يصل إلى عتبة فسيولوجية يتباطأ عندها اكتساب الوزن بسبب التكيف الأيضي أو القيود الجينية. ويؤكد تحليل التسارع هذا الاتجاه بشكل أكبر، مع وجود قيم إيجابية خلال التطور المبكر وقيم سلبية خلال المراحل اللاحقة، وهي سمة مميزة للمرحلة المقاربة لمنحنيات النمو السيني، كما هو موضح في النماذج اللوجستية، ونماذج جومبيرتز، وريتشاردز. توضح هذه النتائج أن AKF لا يناسب البيانات المرصودة بدقة فحسب، بل يكشف أيضًا عن التحولات الكامنة في سلوك النمو، مما يوفر أداة قوية للرصد والتحليل في الوقت الفعلي في دراسات التطور البيولوجي.