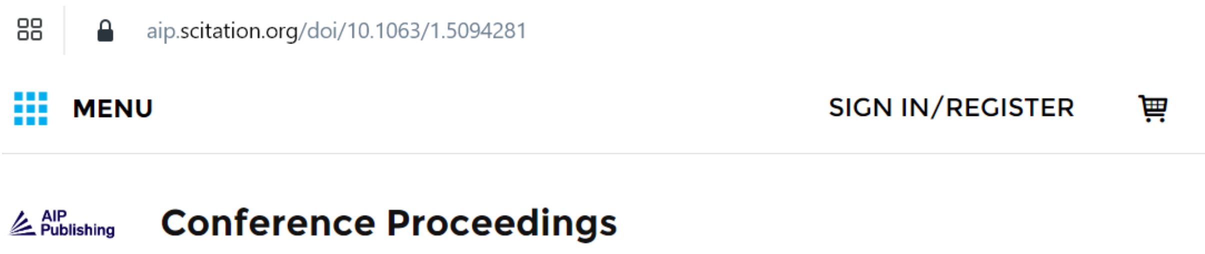
A comparison of continuous genetic algorithm and particle swarm optimization in parameter estimation of Gompertz growth model

Windarto, Eridani, Utami Dyah Purwati



AIP Conference Proceedings **2084**, 020017 (2019)

https://aip.scitation.org/doi/pdf/10.1063/1.5094281

https://doi.org/10.1063/1.5094281

ISSN: 0094243X

Scopus

Documents

Export Date: 08 Jan 2023

Search:

1) Windarto, Eridani, Purwati, U.D.

A comparison of continuous genetic algorithm and particle swarm optimization in parameter estimation of Gompertz growth model

(2019) AIP Conference Proceedings, 2084, art. no. 020017, . Cited 5 times.

1) https://www.scopus.com/inward/record.uri?eid=2-s2.0-85063894077&doi=10.1063%2f1.5094281&partnerID=40&md5=4bb6e89

DOI: 10.1063/1.5094281

Document Type: Conference Paper

Publication Stage: Final

Source: Scopus

Source details

AIP Conference Proceedings

Scopus coverage years: from 1973 to 1978, from 1983 to 1984, 1993, from 2000 to 2001, from 2003 to 2022

ISSN: 0094-243X E-ISSN: 1551-7616

Subject area: Physics and Astronomy: General Physics and Astronomy

Source type: Conference Proceeding

View all documents > Set document alert Save to source list

CiteScore 2021
0.8

SJR 2021
0.189

SNIP 2021
0.262

CiteScore CiteScore rank & trend Scopus content coverage

i Improved CiteScore methodology

CiteScore 2021 counts the citations received in 2018-2021 to articles, reviews, conference papers, book chapters and data papers published in 2018-2021, and divides this by the number of publications published in 2018-2021. Learn more >

CiteScore 2021

$$0.8 = \frac{\text{34,444 Citations 2018 - 2021}}{\text{43,453 Documents 2018 - 2021}}$$

Calculated on 05 May, 2022

CiteScoreTracker 2022

$$0.7 = \frac{\text{28,817 Citations to date}}{\text{40,470 Documents to date}}$$

Last updated on 06 December, 2022 • Updated monthly

CiteScore rank 2021

Category	Rank	Percentile
Physics and Astronomy — General Physics and Astronomy	#194/240	19th

View CiteScore methodology > CiteScore FAQ > Add CiteScore to your site

AIP Conference Proceedings

COUNTRY

United States

Universities and research institutions in United States

SUBJECT AREA AND CATEGORY

Physics and Astronomy
- Physics and Astronomy (miscellaneous)

PUBLISHER

American Institute of Physics

H-INDEX

75

PUBLICATION TYPE

Conferences and Proceedings

ISSN

0094243X, 15517616

COVERAGE

1973-1978, 1983-1984, 1993, 2000-2001, 2003-2021

INFORMATION

Homepage

How to publish in this journal

confproc@aip.org

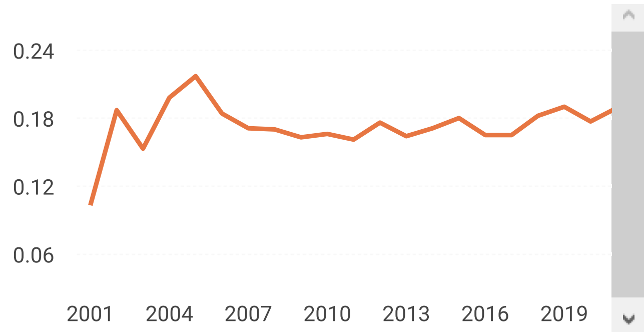
SCOPE

Today, AIP Conference Proceedings contain over 100,000 articles published in 1700+ proceedings and is growing by 100 volumes every year. This substantial body of scientific literature is testament to our 40-year history as a world-class publishing partner, recognized internationally and trusted by conference organizers worldwide. Whether you are planning a small specialist workshop or organizing the largest international conference, contact us, or read these testimonials, to find out why so many organizers publish with AIP Conference Proceedings.

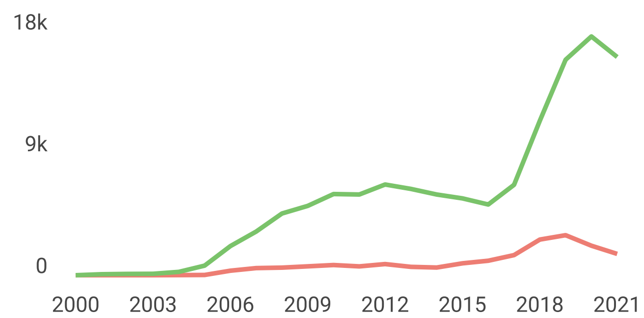
Join the conversation about this journal

SJR

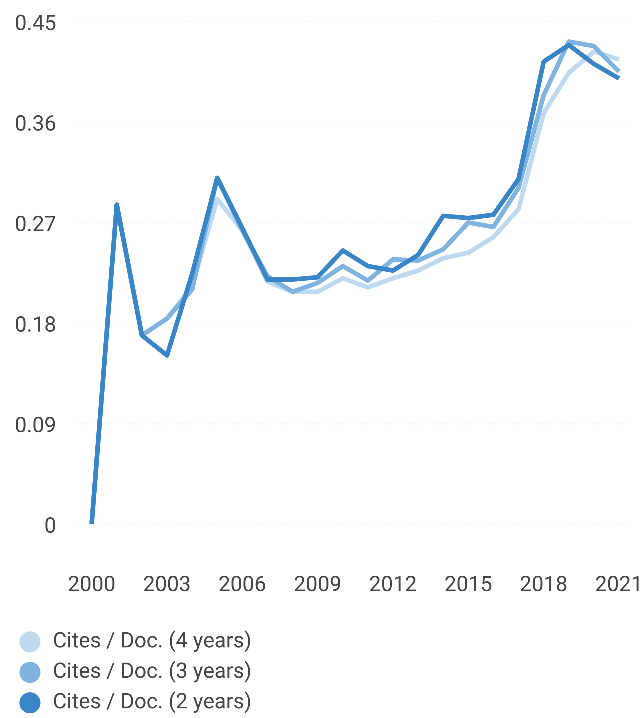
Total Documents



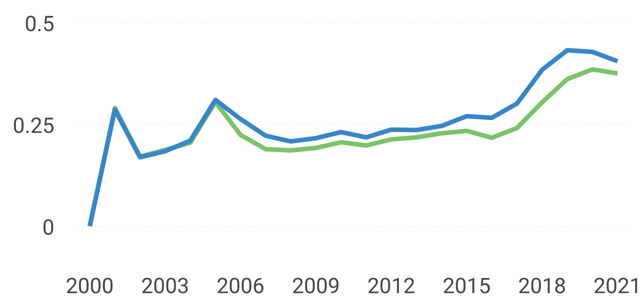
Total Cites Self-Cites



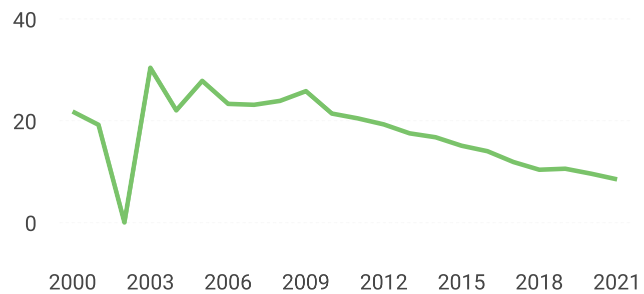
Citations per document



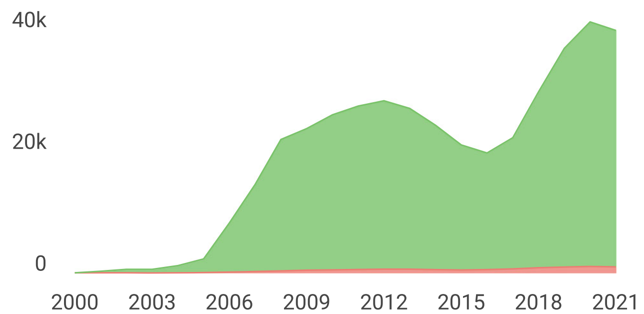
External Cites per Doc Cites per Doc



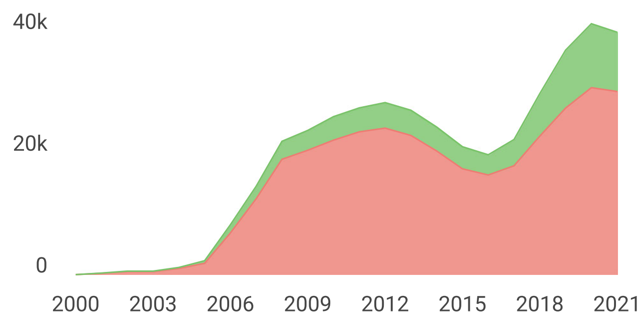
% International Collaboration



Citable documents Non-citable documents



Cited documents Uncited documents



← Show this widget in your own website

Just copy the code below and paste within your html code:

<a href="https://www.scimag

Metrics based on Scopus® data as of April 2022

Preface: Proceedings of the Symposium on BioMathematics (SYMOMATH) 2018

Cite as: AIP Conference Proceedings **2084**, 010001 (2019); https://doi.org/10.1063/1.5094264
Published Online: 22 March 2019

Preface: Proceedings of the Symposium on BioMathematics (SYMOMATH) 2018

The International Symposium on BioMathematics (Symomath) 2018 is jointly organized by Department of Mathematics, Universitas Indonesia and the Indonesian Biomathematical Society. It was held on August 31st- September 2nd, 2018 at Savero Hotel, Depok, Indonesia.

Symomath 2018 is a multidisciplinary forum for promoting and fostering interactions between mathematical, biological and related industrial communities in studying various phenomena in biology, ecology, infectious diseases, medicine, bioengineering, environmental sciences, etc.

The scope of this conference is, but not limited to, in the fields of: Bioinformatics and Systems Biology, Bioengineering and Synthetic Biology, Dynamics of infectious diseases transmission, Dynamics of renewable resources, Biological population, Controlling infectious diseases, Bio-statistics, Utilizing renewable resources in fishery and forestry industries, Bio-mathematics with economic and conservation issues.

At Symomath 2018, 75 registered participants, 7 Plenary talks, 12 invited talks, 25 participants and 41 contributed papers were presented at the symposium.

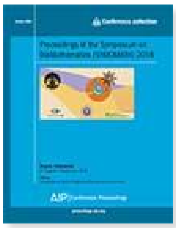
We would like to express our deep appreciation to our sponsors: Universitas Indonesia and Indonesia Re, and also to Universitas Gunadarma, BPJS Kesehatan and AIA that also support the symposium.

At the end of this preface, we would like to thanks to all Symomath 2018 committee members for their hard works and tremendous support, and to all participants.

Proceedings of the Symposium on BioMathematics (SYMOMATH) 2018
AIP Conf. Proc. 2084, 010001-1–010001-1; https://doi.org/10.1063/1.5094264
Published by AIP Publishing. 978-0-7354-1814-1/$30.00

Table of Contents

PROCEEDINGS OF THE SYMPOSIUM ON BIOMATHEMATICS (SYMOMATH) 2018



Conference date: 31 August–2 September 2018
Location: Depok, Indonesia
ISBN: 978-0-7354-1814-1
Editors: Hengki Tasman, Bevina Desjwiandra Handari and Hiromi Seno
Volume number: 2084
Published: Mar 22, 2019

PRELIMINARY

AIP Conference Proceedings **2084**, 010001 (2019); https://doi.org/10.1063/1.5094264

ARTICLES

No Access . March 2019

Leslie-Gower predator-prey model with stage-structure, Beddington-DeAngelis functional response, and anti-predator behavior

U. Salamah, A. Suryanto and W. M. Kusumawinahyu

AIP Conference Proceedings **2084**, 020001 (2019); https://doi.org/10.1063/1.5094265

SHOW ABSTRACT

No Access . March 2019

A stage-structure predator-prey model with ratio-dependent functional response and anti-predator

A. Apriyani, I. Darti and A. Suryanto

AIP Conference Proceedings **2084**, 020002 (2019); https://doi.org/10.1063/1.5094266

SHOW ABSTRACT

No Access . March 2019

Multivariate adaptive regression spline in Ischemic and Hemorrhagic patient (case study)

Ria Dhea L. N. Karisma and Sri Harini

AIP Conference Proceedings **2084**, 020003 (2019); https://doi.org/10.1063/1.5094267

SHOW ABSTRACT

No Access . March 2019

Implementation of factor analysis for bicluster acquisition: Sparseness projection (FABIAS) on microarray of Alzheimer's gene expression data

Theresia B. P. Wutun, Alhadi Bustamam and Titin Siswantining

AIP Conference Proceedings **2084**, 020004 (2019); https://doi.org/10.1063/1.5094268

SHOW ABSTRACT

No Access . March 2019

Finding correlated bicluster from gene expression data of Alzheimer disease using FABIA biclustering method

Nuning Setyaningrum, Alhadi Bustamam and Titin Siswantining

AIP Conference Proceedings **2084**, 020005 (2019); https://doi.org/10.1063/1.5094269

SHOW ABSTRACT

No Access . March 2019

Differential gene co-expression network using BicMix

N. A. Wibawa, Alhadi Bustamam and Titin Siswantining

AIP Conference Proceedings **2084**, 020006 (2019); https://doi.org/10.1063/1.5094270

SHOW ABSTRACT

No Access . March 2019

Armed forces population dynamics: The effect of movement in state border

A. Triska, H. Widayani and N. Nuraini

AIP Conference Proceedings **2084**, 020007 (2019); https://doi.org/10.1063/1.5094271

SHOW ABSTRACT

No Access . March 2019

A biclustering procedure using BicBin algorithm for HIV-1 human protein interaction database in NCBI

Patuan Pangihutan Tampubolon, Alhadi Bustamam, Dian Lestari and Wibowo Mangunwardoyo

AIP Conference Proceedings **2084**, 020008 (2019); https://doi.org/10.1063/1.5094272

SHOW ABSTRACT

No Access . March 2019

Optimal control of innate immune response on lung-macrophages in pneumonia

Usman Pagalay, Dewi Zumrotul Nafisa and Heni Widayani

AIP Conference Proceedings **2084**, 020009 (2019); https://doi.org/10.1063/1.5094273

SHOW ABSTRACT

No Access . March 2019

Dynamical analysis of a tumor growth model involving interferon gamma

I. J. T. R. Tamsih, Trisilowati and U. Habibah

AIP Conference Proceedings **2084**, 020010 (2019); https://doi.org/10.1063/1.5094274

SHOW ABSTRACT

No Access . March 2019

Protein sequence analysis of the Zika virus and the dengue virus using Smith Waterman algorithm

Mohammad Syaiful Pradana and Siti Amiroch

AIP Conference Proceedings **2084**, 020011 (2019); https://doi.org/10.1063/1.5094275

SHOW ABSTRACT

No Access . March 2019

Blighted Ovum detection using convolutional neural network

Feni Andriani and Iffatul Mardhiyah

AIP Conference Proceedings **2084**, 020012 (2019); https://doi.org/10.1063/1.5094276

SHOW ABSTRACT

No Access . March 2019

Mathematical model of dengue transmission based on daily data in Bandung

Muhammad Fakhruddin, Nuning Nuraini and Sapto Wahyu Indratno

AIP Conference Proceedings **2084**, 020013 (2019); https://doi.org/10.1063/1.5094277

SHOW ABSTRACT

No Access . March 2019

Imitation game dynamics of vaccine-decision making behaviour on dengue transmission dynamics

Meksianis Z. Ndii, Nursanti Anggriani and Asep K. Supriatna

AIP Conference Proceedings **2084**, 020014 (2019); https://doi.org/10.1063/1.5094278

SHOW ABSTRACT

BROWSE VOLUMES

No Access . March 2019

Biclustering protein interactions between HIV-1 proteins and humans proteins using LCM-MBC algorithm

Olivia Swasti, Alhadi Bustamam, Dian Lestari and Wibowo Mangunwardoyo

AIP Conference Proceedings **2084**, 020015 (2019); https://doi.org/10.1063/1.5094279

SHOW ABSTRACT

No Access . March 2019

POLS algorithm to find a local bicluster on interactions between HIV-1 proteins and human proteins

Tesdiq Prigel Kaloka, Alhadi Bustamam, Dian Lestari and Wibowo Mangunwardoyo

AIP Conference Proceedings **2084**, 020016 (2019); https://doi.org/10.1063/1.5094280

SHOW ABSTRACT

No Access . March 2019

A comparison of continuous genetic algorithm and particle swarm optimization in parameter estimation of Gompertz growth model

Windarto, Eridani and Utami Dyah Purwati

AIP Conference Proceedings **2084**, 020017 (2019); https://doi.org/10.1063/1.5094281

SHOW ABSTRACT

No Access . March 2019

Mathematical analysis of a tuberculosis transmission model with vaccination in an age structured population

S. L. Chasanah, D. Aldila and H. Tasman

AIP Conference Proceedings **2084**, 020018 (2019); https://doi.org/10.1063/1.5094282

SHOW ABSTRACT

No Access . March 2019

Numerical analysis of the impact of loss-sight and undetected cases in the spread of TB

Dian Setyorini, Bevina D. Handari and Dipo Aldila

AIP Conference Proceedings **2084**, 020019 (2019); https://doi.org/10.1063/1.5094283

SHOW ABSTRACT

No Access . March 2019

Performance comparison of the convolutional neural network optimizer for photosynthetic pigments prediction on plant digital image

K. R. Prilianti, T. H. P. Brotosudarmo, S. Anam and A. Suryanto

AIP Conference Proceedings **2084**, 020020 (2019); https://doi.org/10.1063/1.5094284

A comparison of continuous genetic algorithm and particle swarm optimization in parameter estimation of Gompertz growth model

Cite as: AIP Conference Proceedings **2084**, 020017 (2019); https://doi.org/10.1063/1.5094281
Published Online: 22 March 2019

Windarto, Eridani, and Utami Dyah Purwati

A Comparison of Continuous Genetic Algorithm and Particle Swarm Optimization in Parameter Estimation of Gompertz Growth Model

Windarto[1,a)], Eridani[1] and Utami Dyah Purwati[1]

[1] *Department of Mathematics, Faculty of Science and Technology, Universitas Airlangga, Indonesia.*

[a)] Corresponding author: windarto@fst.unair.ac.id

Abstract. Genetic algorithm and Particle Swarm Optimization are heuristic optimization methods inspired by genetic principles and swarm behavior phenomena, respectively. Those two methods are initiated by random generation of initial populations (initial solutions), fitness evaluation of every solution, solution updating until a termination condition are met. It is well known that those two methods are not always converge to an optimal solution. Those methods sometimes converge to suboptimal solutions, solution near the optimal solution. In this paper, continuous genetic algorithm and particle swarm optimization were implemented to estimate parameters in the Gompertz growth model from rooster weight data cited from literature. Although the best results of the two models were not significantly differs, we found that the particle swarm optimization method was more robust than the continuous genetic algorithm. Hence, the particle swarm optimization method is more recommended than the continuous genetic algorithm.

Keywords: Gompertz growth model, rooster weight dynamic, parameter estimation, particle swarm optimization.

INTRODUCTION

Mathematical models are useful tool to describe many real problems. A mathematical model is usually began by identification of a real problem. Then one could construct a suitable mathematical model and determining mathematical solution of the model. Finally, one should interpret mathematical solution of the model into real problem points of view. A mathematical model might occur in either a deterministic model or a probabilistic (stochastic) model. Mathematical model validation could be performed whenever relevant data from real phenomena are available. If the predicted results from a mathematical model fit the real data, then the model is said a good model. When the predicted results from the model differ significantly the real data, then the model should be improved and modified.

Most mathematical models contain one or more parameters. The parameters should be estimated in order to accurately perform model simulation. Parameter estimation of a mathematical model could be considered as an optimization problem. Deterministic optimization methods such as conjugate gradient method, Nelder-Mead method or Newton method could be applied to estimate parameters in a mathematical model whenever analytical solution of the model could be presented in closed form [1]. Unfortunately, deterministic optimization methods such as Nelder-Mead or Newton method fail to converge into global minimum of a function if the function has many local minima [2]. Moreover, some mathematical models occur in non-linear ordinary differential equation systems, so exact solution (closed form solution) of the model could not be determined. In this case, heuristic method such as particle swarm optimization and genetic algorithm method could be implemented to estimate parameter values from the models.

Particle swarm optimization and genetic algorithm are optimization methods based on a population-based stochastic search process [3, 4]. Particle swarm optimization methods and modified particle swarm optimization have been widely applied in many areas, including performance improvement of Artificial Neural Network [5, 6], scheduling problems [7, 8], flowshop scheduling problem [9], traveling salesman problem [10], vehicle routing problem [11, 12] and clustering technique [13]. Genetic algorithm has been in parameter estimation in poultry growth model [14, 15] and parameter estimation for dynamical system model [1, 16].

Proceedings of the Symposium on BioMathematics (SYMOMATH) 2018
AIP Conf. Proc. 2084, 020017-1–020017-7; https://doi.org/10.1063/1.5094281
Published by AIP Publishing. 978-0-7354-1814-1/$30.00

Some authors compared performance of particle swarm optimization and genetic algorithm in some research are. Yang et al. compared the methods in a Hidden Markov Model training [17]. Wang et al. have been compared performance of genetic algorithm and particle swarm optimization in relativistic backward wave oscillator [18]. Islam et al. have compared performance of some nature inspired algorithms including genetic algorithm and particle swarm optimization in function optimization of some benchmark functions [19]. In this paper, we compared performance of continuous genetic algorithm and particle swarm optimization in parameter estimation of Gompertz growth model.

The remainder of this paper is organized as follows. Section 2 briefly presents particle swarm optimization and genetic algorithm procedure. Comparison of particle swarm optimization and genetic algorithm in parameter estimation of Gompertz growth model will be presented in Section 3. Finally, conclusions are presented in Section 4.

CONTINUOUS GENETIC ALGORITHM AND PARTICLE SWARM OPTIMIZATION

Genetic algorithm is inspired from principles of genetic and natural selection in a life organism. Therefore, many terms such as gene chromosome, individual, parent, selection, mating, crossover, offspring in genetic algorithm are adopted from biology. From mathematical point of view a gene represents a variable, while a chromosome or an individual represents a solution. Genetic algorithm has at least the following elements, namely populations of chromosomes, selection according to fitness, crossover to produce new offspring, and random mutation of new offspring [20]. Genetic algorithm diagram is presented in the Figure 1. The diagram is adapted from Haupt and Haupt [2].

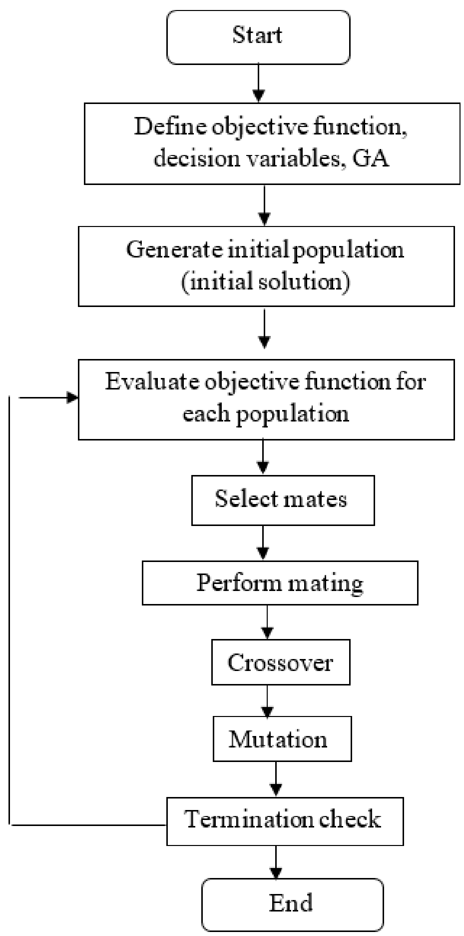


FIGURE 1. Flowchart of continuous genetic algorithm.

We can transform an optimization problem into a minimization problem. Here is genetic algorithm procedure for finding either optimal or suboptimal solution of a minimization problem [2, 16, 20]:

(1) Define the objective function (the cost function) and decision variables related to the optimization problem.
(2) Determine parameter values in genetic algorithm, namely number of generations/number of iteration, crossover probability, and mutation probability/mutation rate.
(3) Generate initial solutions (initial population) from the search space/solution space.
(4) Evaluate cost function of each solution (individual). In a minimization problem, all individuals are ordered from the lowest to the highest of objective function value objectivecost to the highest cost.
(5) Select part of individuals for the next generation as parent individuals. Only the best solutions are maintained for the next generation. The remaining individuals are replaced by better individuals. The selection rate parameter determines the fraction of all population that survives for the next generation. The typical value of selection rate parameter is 50%.
(6) Carry out mating process from parent individuals.
(7) Do crossover process to generate offspring individual.
(8) Perform mutation process to part of solutions to generate solutions.
(9) Test termination condition. If the termination condition did not satisfy yet, then go to the fourth step.

A main problem in the genetic algorithm is premature convergence where the solutions converge to a local optimum. The premature convergence occurs when a high fitness solution (individual) quickly dominate the population. The problem especially occurs in multimodal problems [21, 22]. Hence, genetic algorithm should be implemented many times to obtain the best solution.

Eberhart and Kennedy developed the particle swarm optimization algorithm in 1995. The algorithm has resemblance to genetic algorithm. The algorithm is started by a set random solutions in a solution space. Then the algorithm searches optimal solution by updating the solutions. However, there are no crossover and mutation process in the particle swarm optimization algorithm. In the algorithm, potential solutions (particles) are updated in the solution space by following the current best solution [4].

In the particle swarm optimization method, a solution is represented by position of a particle. We start the particle swarm optimization by randomly selecting initial solutions in a solution space. Then, we evaluate fitness function of current position. We update the local best position of a particle whenever fitness value of current particle is better than the previous best value. We update the global best based on the best fitness value of all particles. Here are the steps of particle swarm optimization algorithm [4, 23]:

(1) Calculate fitness value of every particle. The fitness function is related to the objective function. In a minimization problem, the smaller objective function the the greater fitness value will be.
(2) Update position of local best and global best.
(3) Update particle velocity by using the equation

$$v_i(t+1) = wv_i(t) + c_1 r_1(lbest(t) - x_i(t)) + c_2 r_2(gbest(t) - x_i(t)), \tag{1}$$

Here $v_i(t)$ and $x_i(t)$ are velocity of particle i and position of particle i at time t, while $lbest(t)$ and $gbest(t)$ are local best and global best position at time t. Parameters r_1 and r_2 represent random number between zero and one with uniform distribution.
(4) Update particle position using the following equation

$$x_i(t+1) = x_i(t) + v_i(t+1). \tag{2}$$

The steps are reiterated some termination condition is met.

In Eq. (1), parameters w, c_1, c_2 are inertia weight, cognitive coefficient and social coefficient respectively. The typical value of w between 0.8 and 1.2, while the typical values of c_1 and c_2 are commonly nearly 2. We can apply velocity clamping to avoid particles from moving very distant outside the solution space. For a solution space restricted by the range $[x_{min}, x_{max}]$, the velocity is limited within the range $[-v_{max}, v_{max}]$ where $v_{max} = m(x_{max} - x_{min})$ for some constant $m,\ 0.1 \le m \le 1$. The ending conditions in particle swarm optimization comprises a maximum number of iterations, a number of iterations since the last update of global best solution, or a target fitness value has reached by some particles [23].

In a one dimensional problem, particle swarm optimization converges towards a local optimum for a comparatively wide range of objective functions. In multidimensional problem, it turns out that the swarm might not converge towards a local optimum [24]. Convergence of particle swarm optimization to a local optimum is called premature convergence. The premature convergence is commonly caused by particle velocity decrease in the solution space. Then the particle velocity decrease causes to a total implosion and eventually fitness stagnation of the swarm [25]. Hence, particle swarm optimization method should be implemented many times to obtain the best solution.

A COMPARISON OF CONTINUOUS GENETIC ALGORITHM AND PARTICLE SWARM OPTIMIZATION

In this section, we compared performance of continuous genetic algorithm and particle swarm optimization in parameter estimation of Gompertz growth model. Gompertz growth model is derived from the following Gompertz differential equation

$$\frac{dy}{dt} = ry\ln\left(\frac{K}{y}\right), y(0) = Y_0. \tag{3}$$

Here, $y(t)$ is population size at time t. The exact solution of the Gompertz differential equation in Eq. (3) could be represented as

$$y(t) = \frac{K}{exp(exp(-r(t - t_{inf})))}, \tag{4}$$

where $t_{inf} = \frac{1}{r}\ln\left(\ln\left(\frac{K}{Y_0}\right)\right)$. The Gompertz growth model has three parameters namely intrinsic growth (r), carrying capacity (K), and inflection time (t_{inf}) parameter. From biological point of view, the fastest growth of a population occur at the inflection time.

In this paper, the Gompertz growth model is applied to describe rooster growth where the data is cited from literature [15, 26]. The rooster growth data is shown in the Table 1.

TABLE 1. Means of the rooster weight data (y).

t (days)	y (grams)	t (days)	y (grams)
0	37	42	519.72
3	41.74	45	577.27
6	59.19	48	633.59
9	79.94	51	667.18
12	102.96	54	717.17
15	132.13	57	786.35
18	170.18	71	1069.28
21	206.56	85	1326.49
24	250.71	99	1589.71
27	285.27	113	1859.26
30	324.92	127	2015.44
33	372.83	141	2142.31
36	417.41	155	2220.54
39	469.13	170	2262.63

Since $y(t)$ is the rooster weight at time t, then the carrying capacity parameter (K) could be interpreted as the rooster mature weight or the maximum weight that can be attained by the rooster. Parameters in the Gompertz model (K, r, t_{inf}) are estimated such that the mean absolute percentage error (MAPE)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \widehat{y_i}}{y_i}\right| \tag{5}$$

is maximum. Here n is number of observation data.

We applied continuous genetic algorithm and particle swarm optimization to estimate parameters in the Gompertz growth model. Here, optimal parameters in the Gompertz growth model was found from the following search space

$$\Omega = \left\{(K, r, t_{inf}) \in R^3 : K \in [2000, 5000], r \in [0, 0.1], t_{inf} \in [30, 100]\right\}. \tag{6}$$

We applied particle swarm optimization method described in the previous section with the inertia weight parameter $w = 1$, the cognitive coefficient parameter $c_1 = 2$ and the social coefficient parameter $c_2 = 2$ respectively. We also applied continuous genetic algorithm for various mutation rate (m) namely $m = 0.05, 0.1, 0.2, 0.3, 0.4, 0.5$. For both algorithm, number of population is set to 100 individuals (particles). We applied both methods for 50 trials while for every trial the methods were terminated after 500 iterations. The best estimation results of the particle swarm optimization and the continuous genetic algorithm was presented in the Table 2.

TABLE 2. The best estimation results of the particle swarm optimization and the continuous genetic algorithm.

Methods	K	r	t_{inf}	MAPE
PSO	2468.54	0.023646	60.68	0.039334
GA (m = 0.05)	2445.65	0.023870	60.15	0.039465
GA (m = 0.1)	2435.97	0.023800	60.21	0.039225
GA (m = 0.2)	2437.81	0.023740	60.34	0.039117
GA (m = 0.3)	2468.65	0.023749	60.67	0.039326
GA (m = 0.4)	2444.90	0.023750	60.41	0.039173
GA (m = 0.5)	2468.70	0.023628	60.77	0.039185

m = mutation rate.

Form the Table 2, we found that best result (minimum of MAPE) of the continuous genetic algorithm and the particle swarm optimization method were not significantly differ. The mean average percentage error for the Gompertz growth model obtained from the methods were around 3.9 %. The results indicated that the Gompertz growth model could be applied to describe rooster growth dynamic. It also indicated that particle swarm optimization and continuous genetic algorithm were successfully implemented in parameter estimation of the Gompertz growth model.

Particle swarm optimization and continuous genetic algorithm are essentially probabilistic methods. Hence, the two methods will generally produce different optimal/sub optimal solution in every trial/calculation/experiment. Statistics of the MAPE of the both methods was presented in the Table 3.

TABLE 3. Statistics of Mean Absolute Percentage Error.

Methods	Number of trials	Average of MAPE	Standard deviation	Minimum	Median	Maximum	p-value
PSO	50	0.045661 [a]	0.003743	0.039334	0.045548	0.058081	
GA (m = 0.05)	50	0.092665 [b]	0.051349	0.039465	0.077008	0.267170	
GA (m = 0.1)	50	0.093638 [b]	0.044163	0.039225	0.087674	0.202533	p-value <
GA (m = 0.2)	50	0.084986 [b]	0.037714	0.039117	0.080257	0.244075	0.0005
GA (m = 0.3)	50	0.098225 [b]	0.054169	0.039326	0.084729	0.270992	
GA (m = 0.4)	50	0.092345 [b]	0.066085	0.039173	0.070386	0.400521	
GA (m = 0.5)	50	0.091441 [b]	0.051345	0.039185	0.077055	0.325060	

m = mutation rate.
[a,b] different superscripts showed significant difference between group at the level 0.05.

From the Table 3, we found that the MAPE average of various mutation rate in the continuous genetic algorithm did not significantly differ. Although the best result (minimum of MAPE) of the continuous genetic algorithm and the particle swarm optimization method were not significantly differ, the MAPE average of the particle swarm optimization method was smaller than the continuous genetic algorithms one. We also found that the MAPE variance of the genetic algorithms were more higher than the particle swarm optimization variance. This results indicate that the particle swarm optimization method was more robust than the continuous genetic algorithm.

CONCLUSIONS

We have implemented particle swarm optimization and continuous genetic algorithm in parameter estimation of the Gompertz growth model. Although the best results of the two models were not significantly differs, we found that the particle swarm optimization method was more robust than the continuous genetic algorithm.

ACKNOWLEDGMENTS

This research was financially supported by Ministry of Research, Technology, and Higher Education through "Penelitian Unggulan Perguruan Tinggi" project.

REFERENCES

[1] Tutkun, N., Parameter estimation in mathematical models using the real coded genetic algorithms, Expert Systems with Applications 36, pp. 3342-3345, 2009.
[2] Haupt, R. L. & Haupt, S. E., Practical genetic algorithms, 2nd ed., John Wiley & Sons, 10-13, 2004.
[3] Eberhart R. & Kennedy, J. A new optimizer using particle swarm theory, Proceedings of the Sixth International Symposium on Micro Machine and Human Science, 3943, 1995.
[4] Kuo, R. J., Wang, M. J. & Huang, T. W., An application of particle swarm optimization algorithm to clustering analysis, Soft Computing 15, pp. 533542, 2011.
[5] Salerno, J., Using the particle swarm optimization technique to train a recurrent neural model, Proceedings of the Ninth IEEE International Conference on Tools with Artificial Intelligence, pp 4549, 1997.
[6] Zhang, C., Shao, H. & Li, Y., Particle swarm optimization for evolving artificial neural network, IEEE international conference on systems, man and cybernetics, 24872490, 2000.
[7] Koay, C.A. & Srinivasan, D., Particle swarm optimization-based approach for generator maintenance scheduling. In: Proceedings of the 2003 IEEE swarm intelligence symposium, 167173, 2003.
[8] Weijun, X., Zhiming, W., Wei, Z. & Genke, Y., A new hybrid optimization algorithm for the job-shop scheduling problem, Proceedings of the 2004 American Control Conference, 55525557, 2004.
[9] Liao, C. J., Chao-Tang Tseng, Luarn, P., A discrete version of particle swarm optimization for flowshop scheduling problems, Computers and Operations Research Vol. 34, No. 10, pp. 3099-3111, 2017.
[10] Wang, K.P., Huang, L., Zhou, C.G. & Pang, W., Particle swarm optimization for traveling salesman problem, 2003 International Conference on Machine Learning and Cybernetics, 15831585, 2003.
[11] Wu, B., Yanwei, Z., Yaliang, M., Hongzhao, D. & Weian, W., Particle swarm optimization method for vehicle routing problem, Fifth World Congress on Intelligent Control and Automation, 22192221, 2004.
[12] Xiao, J.M., Li, J.J., Wang, X.H., Modified particle swarm optimization algorithm for vehicle routing problem, Jisuanji Jicheng Zhizao Xitong (Computer Integrated Manufacturing Systems) Vol. 11 No. 4, pp. 577-581, 2005.
[13] Niu, B., Duan, Q., Liu, J., Tan, L. , Liu, Y., A population-based clustering technique using particle swarm optimization and k-means, Natural Computing Vol 16. No. 1: 45-59, 2017.
[14] Roush, W.B. & Branton, S. L., A Comparison of Fitting Growth Models with a Genetic Algorithm and Nonlinear Regression, Poultry Science 84, pp. 494502, 2005.
[15] Windarto, Indratno, S. W., Nuraini, N., & Soewono, E., A comparison of binary and continuous genetic algorithm in parameter estimation of a logistic growth model, AIP Conference Proceedings 1587, 139142, 2014.
[16] Windarto, An implementation of continuous genetic algorithm in parameter estimation of predator-prey model, AIP Conference Proceedings 1718, 2016.
[17] Yang, F., Zhang, C., Sun, T., Comparison of Particle Swarm Optimization and Genetic Algorithm for HMM training, Proceedings - International Conference on Pattern Recognition 2008, 2008.
[18] Wang, H., Liu, D., Meng, L., Liu, L., Particle swarm optimization and genetic algorithm for a relativistic backward wave oscillator, Jisuan Wuli (Chinese Journal of Computational Physics) Vol. 31, No. 4, pp. 479-485, 2014.
[19] Islam, M.J., Tanveer, M.S.R., Akhand, M.A.H., A comparative study on prominent nature inspired algorithms for function optimization, 5th International Conference on Informatics, Electronics and Vision (ICIEV) 2016, 7760112, pp. 803-808, 2016.
[20] Mitchell, M., An Introduction to Genetic Algorithms, MIT Press, 1-10, 1999.
[21] Nicoara, E.S., Mechanisms to Avoid the Premature Convergence of Genetic Algorithms, Buletinul Universitaţii Petrol - Gaze din Ploieşti 61(1):87-96, 2009.
[22] Malik, S., Wadhwa, S., Preventing Premature Convergence in Genetic Algorithm Using DGCA and Elitist Technique, International Journal of Advanced Research in Computer Science and Software Engineering 4(6): 410-418, 2014.

[23] Rini, D.P., Shamsuddin, S.M., Yuhaniz, S.S., Particle Swarm Optimization: Technique, System and Challenges, International Journal of Computer Applications 14(1), 2011.
[24] Schmitt, B.I., Convergence Analysis for Particle Swarm Optimization, FAU University Press, Erlangen, 2015.
[25] Ye, H., Luo, W., Li, Z., Convergence Analysis of Particle Swarm Optimizer and Its Improved Algorithm Based on Velocity Differential Evolution, Computational Intelligence and Neuroscience Volume 2013, Article ID 384125, 2013.
[26] Aggrey, S.E., Comparison of Three Nonlinear and Spline Regression Models for Describing Chicken Growth Curves, Poultry Science 81:1782-1788, 2002.