HIBISCUS

BIOREMEDIATION SCIENCE & TECHNOLOGY RESEARCH

Website: http://journal.hibiscuspublisher.com/index.php/BSTR

Short Communication

Test for the Presence of Autocorrelation in the Gompertz Model used in the Fitting of the Growth of *E. coli* Measured using a Real-time Impedimetric Biosensor

Shukor, M.S.[1] and Shukor, M.Y.*[1,2]

[1]Snoc International Sdn Bhd, Lot 343, Jalan 7/16 Kawasan Perindustrian Nilai 7, Inland Port, 71800, Negeri Sembilan, Malaysia.
[2]Department of Biochemistry, Faculty of Biotechnology and Biomolecular Sciences, Universiti Putra Malaysia, UPM 43400 Serdang, Selangor, Malaysia.

*Corresponding author: yunus.upm@gmail.com
Faculty of Biotechnology and Biomolecular Sciences,
Universiti Putra Malaysia,
UPM 43400 Serdang,
Selangor, Malaysia
Tel No: +603-89466722

HISTORY

Received: 28st October 2014
Received in revised form: 21st of December 2014
Accepted: 29th of December 2014

KEYWORDS

modified Gompertz model
E. coli
Impedance biosensor
ordinary least squares method
autocorrelation

ABSTRACT

Biosensor for measuring bacterial concentrations for use biotechnology and the health sciences would allow a rapid, robust and sensitive real-time monitoring of bacteria. Kim et al. [1] has developed such a method using impedance spectroscopy, and was able to measure in real-time the concentration of *E. coli* at 0.01 MHz frequency using impedance changes. We modeled the growth kinetics using several nonlinear regression methods and discovered that the modified Gompertz model is the best model for the growth of the bacterium [2]. Bacterial growth curves are time-dependent series model and the use of nonlinear regression method relies heavily on the assumption that the residuals must not show autocorrelation. If this assumption is satisfied than the test is said to be robust. In this work we perform statistical diagnosis test to test for the presence of autocorrelation in this model and found out its absence suggesting that the model is robust enough and adequate.

INTRODUCTION

Impedance spectroscopy utilizes electrical properties of materials and their interfaces with electronically conducting electrodes. It is a relatively novel and powerful method [1,3,4]. The use of this method by Kim et al. [1] for monitoring bacterial growth has been explored and showed promising results. The resultant bacterial growth showed a unique sigmoidal characteristics of bacterial growth including a lag time (λ) followed by an acceleration to a maximal value (μ_m) or exponential phase culminating in a final phase in which the rate decreases and finally reaches zero, so that an asymptote (A) is reached [5].

Of several of the models we used such as the modified Logistic [5,6], modified Gompertz [5,7], modified Richards [5,6], modified Schnute [5,8], Baranyi-Roberts [9] and Von Bertalanffy [10], Buchanan three-phase [11] and Huang model [12], the modified Gompertz was found to be the best [13]. Nonlinear regression using the least square method normally uses the assumption that data points do not depend on each other or the value of a data point is not dependent on the value of preceding or proceeding data points or data must not be autocorrelated. Autocorrelation amongst data can occur due to events such as temperature drift during time measurements or an overused tungsten lamp in a spectrophotometer.

If one were to count the number of animals per year in a given area the data would be highly autocorrelated and nonindependence as the number of animals in a current year would be highly dependent upon the number of animals in the previous year [14]. This is very similar to growth of microorganisms where the increase in cellular number in a given time frame can be exponentially fast and any event in time that effect the current or past number of cells would be seen in an amplified manner in future times.

In this work, the Durbin–Watson statistic for the presence of autocorrelation in the growth of this yeast would be used. The method calculates the level of significance according to the method outlined by Draper and Smith [15].

METHODS

Acquisition of data

Data were acquired from the works of [2]. The reduction kinetics using the modified Gompertz model (**Fig.** 1) was used as before to obtain residuals for the regression.

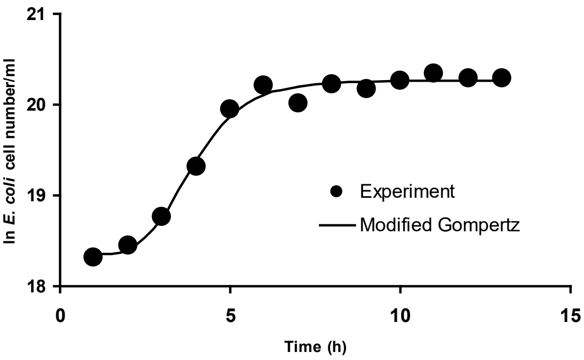

Fig. 1. Growth curve of *E. coli* fitted with the modified Gompertz growth model. The number of cells/ml was transformed into natural logarithm.

Durbin-Watson test

The Durbin–Watson statistic calculates the level of significance according to the method outlined by Draper and Smith [15].

$$d = \frac{\sum_{t=2}^{T}\left(\hat{e}_t - \hat{e}_{t-1}\right)^2}{\sum_{t=1}^{T}\hat{e}_t^2} \qquad (1)$$

As usual the hypothesis H_0: $\rho = 0$ versus the alternative $H1$: $\rho > 0$ is tested. The statistic is approximately equal to $2(1-p)$. The Durbin-Watson test statistic equals 2 when the ρ value is zero while a ρ value of one equals a Durbin-Watson test statistic of 0. Non-autocorrelation is indicated by a d value near 2 while a value towards 0 indicates positive autocorrelation. Negative autocorrelation is indicated by d values nearing 4 (Eq. 1).

The null hypothesis should be rejected for a low value of the Durbin-Watson test statistic indicating significant autocorrelation. Unlike the t- or z-statistics, the distribution of the Durbin-Watson test statistic is not available for ρ-value associated with d and tables must be used in the hypothesis testing.

The decision rule for the Durbin-Watson bounds test is
• if d > upper bound, fail to reject the null hypothesis of no serial correlation,
• if d < lower bound, reject the null hypothesis and conclude that positive autocorrelation is
present,
• if lower bound < d < upper bound, the test is inconclusive.

RESULTS AND DISCUSSION

The Durbin–Watson statistic (DW) can calculate for the presence of serial correlation of residuals. Autocorrelation, also known as serial correlation, is the cross-correlation of a signal with itself. The DW is used to test whether a model has been successful in describing the underlying trend. Informally, it is the similarity between observations as a function of the time lag between them. It is a mathematical tool for finding repeating patterns, such as the presence of a periodic signal obscured by noise. This is because most regression problems involving time series data exhibit positive autocorrelation. Autocorrelation amongst data can occur due to events such as temperature drift during time measurements or an overused tungsten lamp in a spectrophotometer. If one were to count the number of animals per year in a given area the data would be highly autocorrelated and nonindependence as the number of animals in a current year would be highly dependent upon the number of animals in the previous year [14–16].

The value of the Durbin-Watson statistics was d= 0.177263/0.078422=2.603. As usual the hypothesis H_0: $\rho = 0$ versus the alternative $H1$: $\rho > 0$ is tested. The statistic is approximately equal to $2(1-p)$. The Durbin-Watson test statistic equals 2 when the ρ value is zero while a ρ value of one equals a Durbin-Watson test statistic of 0. Non-autocorrelation is indicated by a d value near 2 while a value towards 0 indicates positive autocorrelation. Negative autocorrelation is indicated by d values nearing 4. The null hypothesis should be rejected for a low value of the Durbin-Watson test statistic indicating significant autocorrelation.

Unlike the t- or z-statistics, the distribution of the Durbin-Watson test statistic is not available for ρ-value associated with d and tables must be used in the hypothesis testing. The upper critical value d_U is 2.102 while the lower critical value d_L is 0.229. Since d was larger than the upper critical value then the null hypothesis is not rejected i.e. there appears to be no evidence of autocorrelation and the modified Gompertz model used for fitting the growth curve is adequate.

ACKNOWLEDGEMENT

This project was supported by a grant from Snoc International Sdn Bhd.

REFERENCES

[1] Kim Y-H, Park J-S, Jung H-I. An impedimetric biosensor for real-time monitoring of bacterial growth in a microbial fermentor. Sens Actuators B Chem. 2009; 138(1):270–7.
[2] Shukor MS, Shukor MY. Submitted to Nanobio and Bionano in December 2014. Nanobio Bionano. 2014;
[3] Dweik M, Stringer RC, Dastider SG, Wu Y, Almasri M, Barizuddin S. Specific and targeted detection of viable *Escherichia coli* O157:H7 using a sensitive and reusable impedance biosensor with dose and time response studies. Talanta. 2012; 94:84–9.
[4] Ward AC, Connolly P, Tucker NP. *Pseudomonas aeruginosacan* be detected in a polymicrobial competition model using impedance spectroscopy with a novel biosensor. PLoS ONE. 2014; 9(3).
[5] Zwietering MH, Wit JCD, Cuppers HGAM, Riet KV. Modeling of bacterial growth with shifts in temperature. 1994; 60(1):204–13.
[6] Ricker FJ. A flexible growth function for empirical use. J Exp Bot. 1959; 10:290–300.
[7] Gompertz B. On the nature of the function expressive of the law of human mortality, and on a new mode of determining the value of life contingencies. PhilosTransRSocLondon. 1825; 115:513–85.
[8] Schnute J. A versatile growth model with statistically stable parameters. Can J Fish Aquat Sci. 1981; 38:1128–40.
[9] Baranyi J. Mathematics of predictive food microbiology. Int J Food Microbiol. 1995; 26(2):199–218.

[10] Bertalanffy L von. heoretische Biologie, Zweiter Band: Stoffwechsel,Wachstum. A FranckeAG Verlag, Bern, Switzerland; 1951. 418 p.
[11] Buchanan RL, Golden MH. Model for the non-thermal inactivation of *Listeria monocytogenes* in a reduced oxygen environment. Food Microbiol. 1995; 12:203–12.
[12] Huang L. Optimization of a new mathematical model for bacterial growth. Food Control. 2013; 32(1):283–8.
[13] Abd Rachman AR, Halmi MIE, Shukor MY. Amplification of new isolated luciferase gene from marine *Photobacterium* strain MIE by using specific PCR. J Environ Microbiol Toxicol. 2014; 2(1):35–7.
[14] Mcdonald JH, Dunn KW. Statistical tests for measures of colocalization in biological microscopy. J Microsc. 2013; 252(3):295–302.
[15] Draper NR, Smith H. Applied Regression Analysis. Wiley, New York; 1981.
[16] Motulsky HJ, Ransnas LA. Fitting curves to data using nonlinear regression: a practical and nonmathematical review. FASEB J Off Publ Fed Am Soc Exp Biol. 1987; 1(5):365–74.