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Short Communication

Test for the Presence of Autocorrelation in the Modified Gompertz Model Used in Fitting of *Burkholderia* sp. strain Neni-11 Growth on Acrylamide

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ABSTRACT

The growth of microorganism on substrates, whether toxic or not usually exhibits sigmoidal pattern. This sigmoidal growth pattern can be modelled using primary models such as Logistic, modified Gompertz, Richards, Schnute, Baranyi-Roberts, Von Bertalanffy, Buchanan three-phase and Huang. Previously, the modified Gompertz model was chosen to model the growth of *Burkholderia* sp. strain Neni-11 on acrylamide, which shows a sigmoidal curve. The modified Gompertz model relies on the ordinary least squares method, which in turn relies heavily on several important assumptions, which include that the data does not show autocorrelation. In this work we perform statistical diagnosis test to test for the presence of autocorrelation using the Durbin-Watson test and found that the model was adequate and robust as no autocorrelation of the data was found.

INTRODUCTION

Microorganisms' growth on toxic substrate exhibits a significant lag phase due to the needs of the cell to tolerate and initiate detoxification and degradation of enzymes upon exposure to toxic substances before integration of the substrates into growth and energy producing processes can take place. Usually, a sigmoidal growth profile that exhibits lag time (λ), acceleration to a maximal value (μm) and a final phase where the rate decreases and eventually reaches zero or an asymptote (A) are observed [1].

The maximum growth rate (μm) is important for the development of secondary models such as growth kinetics. The sigmoidal curve can be fitted by different mathematical functions, such as Logistic [1,2], modified Gompertz [1,3], Richards [1,4], Schnute [1,5], Baranyi-Roberts [6], Von Bertalanffy [1,7–9], Buchanan three-phase [10,11] and more recently the Huang models [12–15]. The modified Gompertz model has been very popular as it can fit various growth curves very well and has been utilized as the first choice of model without resorting to the comparative use of other models [16–27].

The least square technique is employed in normal nonlinear regression with the central idea that data points usually do not rely on one another or the value of a data point is not determined by the value of previous or proceeding data points. However, in certain cases this do not occur as the presence of autocorrelation amongst data may appear. The best example of autocorrelation is temperature drift in the course of time measurements affecting negatively or positively the outcome of the measurements in a series of discernible pattern. Another example includes an over-used tungsten lamp in a spectrophotometer.

In other cases, autocorrelation cannot be avoided as in the example where the quantity of creatures per year in a given area will be highly autocorrelated and dependent on the quantity of creatures in the last year [28]. This is extremely comparable to the expansion of bacteria in which the rise in cellular quantity with respect to time is usually significantly fast and then for any event in time that impact the present or past quantity of cells will be observed in an increased way in the future. One of the most often method to check for the presence of autocorrelation is the Durbin–Watson statistic.

The method calculates the level of significance according to the method outlined by Draper and Smith [29–31]. In a previous study, the modified Gompertz model was chosen to model the growth of *Burkholderia* sp. strain Neni-11 on acrylamide [26]. In order to test for the adequacy of the model as far as autocorrelation is concerned, the Durbin-Watson test was utilized in this study.

METHODS

Acquisition of Data

Data on the growth of the bacterium *Burkholderia* sp. strain Neni-11 on acrylamide from Figure 6 as modelled using the modified Gompertz model from our previous works [26]was utilized in this study (Fig. 1).

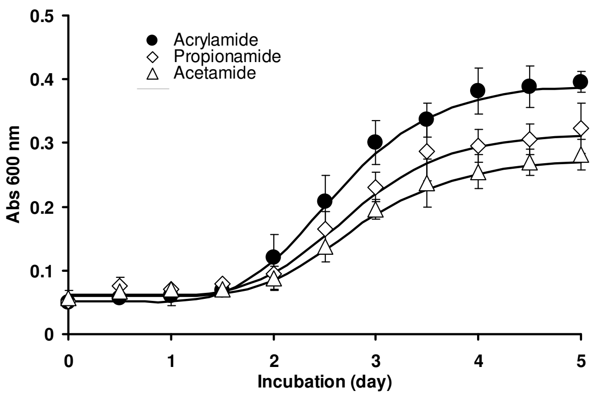

Fig 1. Growth of *Burkholderia* sp. strain Neni-11 on acrylamide, propionamide and acetamide as modelled using the modified Gompertz model (solid lines) (Fig. 6 from [26] reproduced with permission from Hibiscus Publisher).

Durbin-Watson test

In the Durbin–Watson test, a statistical calculation is carried out to test for the level of significance [30].

In this test, the usual hypothesis where H_0: ρ= 0 versus the alternative $H1$: $\rho > 0$ is performed. The statistic is approximately equal to 2(1− p). A ρ value is zero is equal to a Durbin-Watson test statistic of 2 when the while a ρ value of one equals a Durbin-Watson test statistic of 0. A d value near 2 indicated non-autocorrelation while positive autocorrelation occurs when a d value towards 0 is obtained. A d values nearing 4 indicates negative autocorrelation (**Eqn. 1**).

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

(**Eqn. 1**)

Once a low value for the Durbin-Watson test statistics is obtained, the null hypothesis should be rejected as this indicates a significant presence of autocorrelation. Unlike As there is no distribution of the ρ-value in the Durbin-Watson test statistics associated with d like the t- or z-statistics, the use of tables in hypothesis testing is mandatory.

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 value of the Durbin-Watson statistics was d 0.046/0.024=1.941. The statistic is approximately equal to 2(1−p). We then test the hypothesis H0: ρ= 0 versus the alternative hypothesis of H1: ρ > 0. From the Durbin-Watson table [29,32] the lower critical value for dL was 0.340, while the upper critical value dU was 1.733. Based on this, the d value was larger than the upper critical value or dU, and this results in the null hypothesis not being rejected or it can be said that there is not any evidence of the presence of autocorrelation. This shows that the modified Gompertz model utilize in the nonlinear regression model governing the growth of this bacterium on acrylamide can be accepted.

Autocorrelated data causes the removal of the degrees of freedom from inferential tests statistics and results in the presence of spurious correlations between variables [33]. The use of the Durbin Watson test for testing the presence of autocorrelation data in time series is abundant in primary modelling exercise such as in the modified Gompertz and other models [24,34–37].

Another technique for detecting autocorrelation is the Breusch-Godfrey Lagrange Multiplier Test. Once autocorrelation is detected, the experimenter might remedy the situation through several transformation methods such as through the use of the Cochrane-Orcutt procedure [38], Hildreth-Lu, or Prais-Winsten that can remedy autocorrelation [39].

CONCLUSION

The presence of autocorrelation in time series data can seriously affect the quality of the regression leading to inaccurate values of parameters. The use of statistical test to detect autocorrelation is vital so that necessary remedy can be carried out. The use of the modified Gompertz model in modelling the growth of a bacterium on acrylamide was tested for the presence of autocorrelation in this study and the results show that the model does not exhibit the presence of autocorrelation, and hence, is an adequate model.

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