

Kinetic Analysis of the Adsorption of Lead(II) onto an Antarctic Sea-Ice Bacterial Exopolysaccharide

Faggo Abdullahi Adamu¹, Hartinie Marbawi^{2*}, Ahmad Razi Othman³, Nur Adeela Yasid¹ and Mohd Yunus Shukor¹

¹Department of Biochemistry, Faculty of Biotechnology and Biomolecular Sciences, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, D.E, Malaysia.

²Biotechnology Programme, Faculty of Science and Natural Resources, Universiti Malaysia Sabah, 88400 Kota Kinabalu, Sabah.

³Department of Chemical Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor, D.E, Malaysia.

*Corresponding author:

Hartinie Marbawi,

Biotechnology Programme,

Faculty of Science and Natural Resources,

Universiti Malaysia Sabah,

88400 Kota Kinabalu, Sabah, Malaysia

Email: hartinie@ums.edu.my

HISTORY

Received: 15th April 2022
Received in revised form: 20th June 2022
Accepted: 21st July 2022

KEYWORDS

Antarctic sea-ice bacterial exopolysaccharide
Biosorption
Lead(II)
Kinetics,
Pseudo-1st order,
Pseudo-2nd order

ABSTRACT

Hypertension and kidney impairment are two of the many adult health problems that have been related to lead exposure. Women who are expecting a child are especially susceptible to the dangers of lead since it can have devastating consequences on the developing embryo. Existing techniques for the remediation of lead pollutant include membrane separation, ion exchange, precipitation and biosorption. Of all of this technology, biosorption has several positive aspects which include low operating expenses, very efficient detoxification of toxicants at low concentrations and low amount of disposal materials. The biosorption of the biosorption of lead(II) onto an Antarctic sea-ice bacterial exopolysaccharide is remodeled using nonlinear regression and the optimal mode was determined by a series of error function assessments. Statistical analysis showed that the best kinetic model for adsorption in salt-free water was pseudo-1st order while the best kinetic model for adsorption in seawater was pseudo-2nd order model. All error function analyses also supported these two best models. The kinetic constants values for salt-free water and seawater shows large difference in terms of adsorption in salt-free water and seawater. A higher equilibrium biosorption capacity for lead (II) or q_e values were exhibited for both k_1 and k_2 rate constants in sea water indicating a more efficient adsorption in seawater. Adsorption in seawater increased the q_e values from 51.11 (mg/g) (95% confidence interval from 49.75 to 52.44) to 92.98 (mg/g) (95% C.I. from 91.01 to 94.95) In addition, the h value, (mg/g.min) indicates a stronger driving force to accelerate the diffusion of adsorbate from seawater onto the adsorbent. The results suggest fundamental difference of sorption mechanism and functional groups are involved in salt-free and seawater.

INTRODUCTION

Mining, electroplating, alloy preparation, pulp-paper, fertiliser, and other industrial operations are releasing heavy metals into the environment at an increasing rate. The accumulation of heavy metals in the food chain and the severe health concerns they cause to living beings have made the issue of pollution involving these substances of paramount importance [1] Throughout the Earth's crust, lead can be found; it is a naturally occurring hazardous element. Due to its widespread use, it has polluted vast areas, exposed countless people, and seriously affected public health in a number of countries. The mining, smelting, manufacturing, and recycling industries, as well as the

continuous use of lead-based paint and aviation fuel in some nations, are all major contributors to environmental pollution. The production of lead-acid car batteries accounts for more than 85 percent of the world's lead usage. However, lead is also used in a wide variety of other items, including pigments, paints, solder, stained glass, lead crystal glassware, ammunition, ceramic glazes, jewellery, toys, cosmetics, and traditional remedies [2,3]

Lead can be found in drinking water if the pipes carrying the water are made of lead or if the pipes are attached using lead-based solder. Most of the lead used in international trade now comes from recycled sources. Young children are more

susceptible to lead's harmful effects, and it can have long-lasting, devastating effects on their health, especially on their brain and nervous system development. Lead has been linked to an increased risk of hypertension and renal damage in adults. [4–6]. Pregnant women are particularly vulnerable to the effects of lead exposure, which can result in a variety of adverse outcomes for the baby. Lead levels in drinking water that above the legal limit of 0.05 mg/L have been linked to anemia, hepatitis, encephalopathy, and nephritic syndrome [2,7,8]

Biosorption is a promising approach for the removal of heavy metals from wastewater because of its high biosorption capacity and selectivity, low cost, and low environmental risk. Several studies have found that microorganism biomass has a higher affinity for Pb(II) biosorption than other heavy metals such as Cd(II) and Hg(II) [9]. To defend themselves from the extreme cold and high salt of the Antarctic, several microorganisms secrete exopolysaccharides (EPS). When ice melts, the salinity of the water below it can change from sea level to three times that of the ocean above it, exposing the ice-trapped bacteria to hyposaline conditions. It is reasonable to assume that Antarctic EPSs played a significant role in protecting organisms within ice floes from ice-crystal damage, buffering against pH and salinity fluctuations, and alleviating other chemical stresses such heavy metals though the mechanism was not so evident. It has been found that the molecular weight of EPSs produced by sea-ice isolates is 5–50 times higher than the average of other isolated marine EPSs [10–12]. Due to their appealing structure and physicochemical properties, EPSs generated by sea-ice isolates may be useful biosorbents for the removal of heavy metals from saltwater [13].

In order to fully understand the biosorption process of toxicants, it is crucial to assign the kinetics and isotherms of biosorption appropriately. Estimating uncertainty of the parameters of the kinetics, which are often displayed as a 95 percent confidence interval range, can be made more challenging by the linearization of a clearly nonlinear curve, which can cause problems on the error structure of the data [14]. Data transformation for linearization may also introduce error into the independent variable. Additionally, due to differences in the weight given to each data point, the fitted parameter values for the linear and nonlinear versions of the model may be different [15]. In this study the published data from the biosorption of lead(II) onto an Antarctic sea-ice bacterial exopolysaccharide [13] is remodeled using nonlinear regression of several kinetic models (Table 1) and the optimal mode was determined by a series of error function assessments. This modeling analysis was necessitated due to the fact that a linearized modelling version was put forward for the kinetics in the aforementioned published paper.

Table 1. Kinetic models and equation utilized in this study.

Model	Equation	Reference
Pseudo-1 st order	$q_t = q_e(1 - e^{-K_1t})$	[16]
Pseudo-2 nd order	$q_t = \frac{K_2q_e^2t}{(1 + K_2q_e t)}$	[17]
<i>h</i> value	$h = K_2q_e^2$	[17]
Elovich	$q_t = \frac{1}{\beta \ln \alpha \beta} + \frac{1}{\beta \ln t}$	[18]

METHODS

Data acquisition and fitting

Data from Figure 1 from a published work [13] were digitized using the software Webplotdigitizer 2.5 [19]. The accuracy of data digitized with this program has been verified [20,21]. The data were then nonlinearly regressed using the curve-fitting software CurveExpert Professional software (Version 1.6).

Statistical analysis

Commonly used statistical discriminatory methods such as corrected AICc (Akaike Information Criterion), Bayesian Information Criterion (BIC), Hannan and Quinn's Criterion (HQ), Root-Mean-Square Error (RMSE), bias factor (BF), accuracy factor (AF) and adjusted coefficient of determination (R^2).

The RMSE was calculated according to Eq. (1), [14], and smaller number of parameters is expected to give a smaller RMSE values. n is the number of experimental data, Ob_i and Pd_i are the experimental and predicted data while p is the number of parameters.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Pd_i - Ob_i)^2}{n - p}} \quad (\text{Eqn. 1})$$

As R^2 or the coefficient of determination ignores the number of parameters in a model, the adjusted R^2 is utilized to overcome this issue. In the equation (Eqns. 2 and 3), the total variance of the y-variable is denoted by S_y^2 while RMS is the Residual Mean Square.

$$\text{Adjusted } (R^2) = 1 - \frac{RMS}{S_y^2} \quad (\text{Eqn. 2})$$

$$\text{Adjusted } (R^2) = 1 - \frac{(1 - R^2)(n - 1)}{(n - p - 1)} \quad (\text{Eqn. 3})$$

The Akaike Information Criterion (AIC) is based on the information theory. It balances between the goodness of fit of a particular model and the complexity of a model [22]. To handle data having a high number of parameters or a smaller number of values corrected Akaike information criterion (AICc) is utilized [23]. The AICc is calculated as follows (Eqn. 4), where p signifies the quantity of parameters and n signify the quantity of data points. A model with a smaller value of AICc is deemed likely more correct [23].

$$AICc = 2p + n \ln \left(\frac{RSS}{n} \right) + 2(p+1) + \frac{2(p+1)(p+2)}{n-p-2} \quad (\text{Eqn. 4})$$

Aside from AICc, Bayesian Information Criterion (BIC) (Eqn. 5) is another statistical method that is based on information theory. This error function penalizes the number of parameters more strongly than AIC [24].

$$BIC = n \ln \frac{RSS}{n} + k \ln(n) \quad (\text{Eqn. 5})$$

A further error function method based on the information theory is the Hannan–Quinn information criterion (HQC) (Eqn. 6). The HQC is strongly consistent unlike AIC due to the $\ln \ln n$ term in the equation [23];

$$HQC = n \times \ln \frac{RSS}{n} + 2 \times k \times \ln(\ln n) \quad (\text{Eqn. 6})$$

Further error function analysis that originates from the work of Ross [25] are the Accuracy Factor (AF) and Bias Factor (BF). These error functions test the statistical evaluation of models for the goodness-of-fit but do not penalize for number of parameter (Eqns. 7 and 8).

$$\text{Bias factor} = 10 \left(\sum_{i=1}^n \log \left(\frac{Pd_i / Ob_i}{n} \right) \right) \quad (\text{Eqn. 7})$$

$$\text{Accuracy factor} = 10 \left(\sum_{i=1}^n \log \left(\frac{(Pd_i / Ob_i)}{n} \right) \right) \quad (\text{Eqn. 8})$$

RESULTS AND DISCUSSION

The adsorption kinetics data of biosorption isotherm experiment from a published work [13] on the biosorption of lead (II) on an Antarctic sea-ice bacterial exopolysaccharide were analyzed using three models—pseudo-1st, pseudo-2nd and Elovich, and fitted using non-linear regression. The Elovich model was the poorest in fitting the curve based on visual observation (Figs. 1-6). Statistical analysis based on root-mean-square error (RMSE), adjusted coefficient of determination ($\text{adj}R^2$), accuracy factor (AF), bias factor (BF), Bayesian Information Criterion (BIC), corrected AICc (Akaike Information Criterion), and Hannan–Quinn information criterion (HQC) were carried out to find the best model.

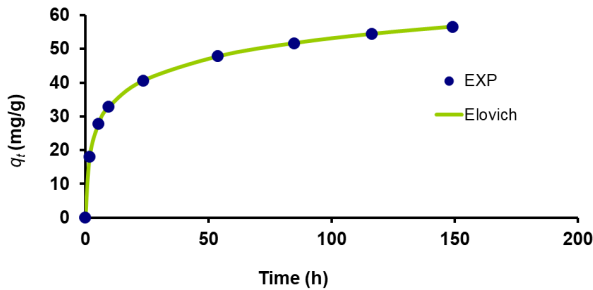


Fig. 1. Kinetics of on the biosorption of lead(II) onto an Antarctic sea-ice bacterial exopolysaccharide in salt-free water modelled using the Elovich model.

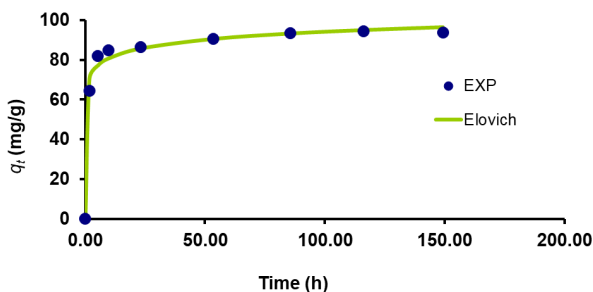


Fig. 2. Kinetics of on the biosorption of lead(II) onto an Antarctic sea-ice bacterial exopolysaccharide in seawater modelled using the Elovich model.

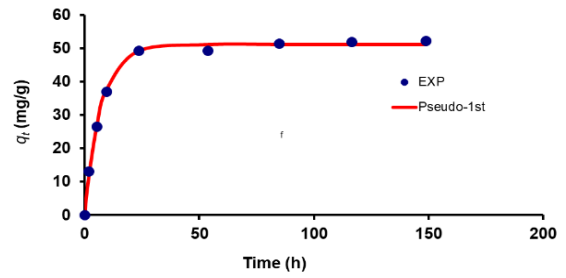


Fig. 3. Kinetics of on the biosorption of lead(II) onto an Antarctic sea-ice bacterial exopolysaccharide in salt-free water modelled using the pseudo-1st order model.

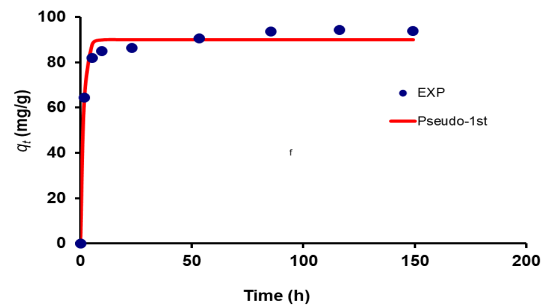


Fig. 4. Kinetics of on the biosorption of lead(II) onto an Antarctic sea-ice bacterial exopolysaccharide in seawater modelled using the pseudo-1st order model.

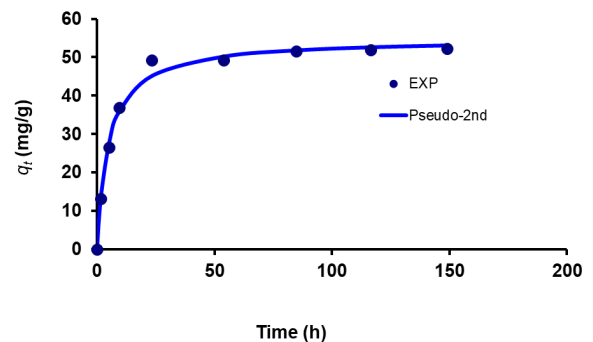


Fig. 5. Kinetics of on the biosorption of lead(II) onto an Antarctic sea-ice bacterial exopolysaccharide in salt-free water modelled using the pseudo-2nd order model.

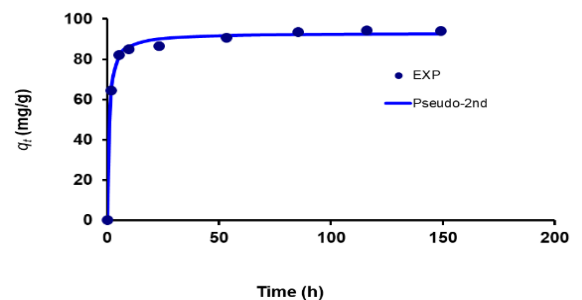


Fig. 6. Kinetics of on the biosorption of lead(II) onto an Antarctic sea-ice bacterial exopolysaccharide in seawater modelled using the pseudo-2nd order model.

The best kinetic model for adsorption in salt-free water was Pseudo-1st with a reasonably large difference in terms of corrected Akaike Information Criterion (>5 absolute unit) to the next best model, which was pseudo-2nd order and the worst model was Elovich (Table 2). On the other hand, the best kinetic model for adsorption in seawater was Pseudo-2nd with also a reasonably large difference in terms of corrected Akaike Information Criterion (>5 absolute unit) to the next best model, which was pseudo-1st order and the worst model was Elovich (Table 3). All error function analyses also supported these two best models.

The kinetic constants values for salt-free water and seawater shows large difference in terms of adsorption in salt-free water and seawater (Table 4). A higher equilibrium biosorption capacity for lead (II) or q_e values were exhibited for both k_1 and k_2 rate constants in sea water indicating a more efficient adsorption in seawater. Adsorption in seawater increased the q_e values from 51.11 (mg/g) (95% confidence interval from 49.75 to 52.44) to 92.98 (mg/g) (95% C.I. from 91.01 to 94.95) In addition, the h value, (mg/g.min) utilized to calculate the initial adsorption rate constant, was also higher in seawater, where a higher h value indicates a stronger driving force to accelerate the diffusion of adsorbate from solution onto the adsorbent [26].

Table 2. Error function analysis for salt-free water kinetic models.

Model	p	RMSE	R^2	adR^2	AICc	BIC	HQC	AF	BF
Pseudo-1 st order	2	1.212	0.997	0.996	16.00	5.60	4.35	1.033	0.984
Pseudo-2 nd order	2	1.857	0.992	0.989	23.68	13.27	12.03	1.035	1.010
Elovich	2	4.567	0.949	0.932	39.88	29.47	28.23	1.100	1.021

Table 3. Error function analysis for seawater kinetic models.

Model	p	RMSE	R^2	adR^2	AICc	BIC	HQC	AF	BF
Pseudo-1 st order	2	4.152	0.983	0.978	38.16	27.76	26.51	1.037	1.000
Pseudo-2 nd order	2	1.832	0.997	0.996	23.43	13.03	11.78	1.015	1.000
Elovich	2	3.525	0.988	0.984	35.22	24.81	23.57	1.028	1.001

Note:
 RMSE Root mean Square Error
 p no of parameters
 adR^2 Adjusted Coefficient of determination
 BF Bias factor
 AF Accuracy factor
 AICc Adjusted Akaike Information Criterion
 BIC Bayesian Information Criterion
 HQC Hannan-Quinn information criterion

Table 4. Calculated constants for salt-free- and seawater kinetic models.

	salt-free water (95%, C.I.)	seawater (95%, C.I.)
Pseudo-1 st		
k_1 (per min)	0.139 (0.123 to 0.155)	0.714 (0.491 to 0.938)
q_e (mg/g)	51.11 (49.753 to 52.441)	89.864 (86.038 to 93.691)
Pseudo-2 nd		
k_2 (g/mg/min)	0.004 (0.003 to 0.005)	0.014 (0.011 to 0.017)
q_e (mg/g)	54.834 (52.213 to 57.456)	92.98 (91.006 to 94.954)
h (mg/g.min)	10.87	188.62
Elovich		
Alpha (mg/g.min)	40.390 (-13.513 to 94.239)	755837.1 (-3289490.3 to 4801164.7)
Beta (g/mg)	0.116 (0.077 to 0.154)	0.174 (0.108 to 0.240)

In order to investigate the mechanism of sorption and possible rate controlling steps for instance chemical reaction and mass transport processes, kinetic models have been used to analyze experimental data. These kinetic models integrated the pseudo-1st order equation, the pseudo-2nd order equation as well as the Elovich equation. For the Elovich model, α represents the initial adsorption rate in mg/g min, while β is the extent of surface coverage in g/mg. The concentration of the adsorbate is set at saturation level in the pseudo-1st order reaction. This results in its level to be constant, and the adsorbate is adsorbed at a constant rate, due to the rate being dependent on a single concentration of the adsorbate. When film diffusion controls the rate, there is an inverse relationship between rate and particle size, the distribution coefficient, and the film thickness. In this situation, the label physisorption is given as the rate-limiting step is diffusion and is independent on the level of both reactant (physical exchange) [27–31].

In the event the reaction is govern by a pseudo-2nd order reaction, chemical reaction controls the rate-controlling step, and when this happen the process is called chemisorption. Under this circumstances, the sorption kinetics matches to a reversible second order reaction at low adsorbate/adsorbent ratios, and at higher sorbate/sorbent ratios, two competitive reversible second order reactions will occur [32]. However, to confirm the mechanism is a chemisorption, further proofs should be provided such as the evaluation results of the activation energies by repeating the experiment at various temperatures and also by checking out the process rates dependences to the sizes of the adsorbent particle [33].

The pseudo-2nd order kinetics model has been reported to be the best model in several lead sorption studies such as lead(II) sorption by *Cephalosporium aphidicola* [34], on sesame leaf [35], on *Spirodela polyrhiza* [36] and on the lead-resistant bacteria *Delftia lacustris* Strain-MS3 [37] to name a few. In general, the pseudo-2nd was the best model for metal sorption such as the biosorption of Cr(VI) to magnetic iron oxide nanoparticle-multi-walled carbon nanotube [38], Cu(II) adsorption onto functionalized cellulose beads from Tunisian almond (*Prunus dulcis*) shell [39] and the sorption of Zn(II) by *Streptomyces ciscaucasicus* [40].

On the other hand, the pseudo-1st order model has also been reported to be the best model for lead(II) sorption onto biobeads immobilised biomass of *P. laurentii* strain RY1 [41], coco-peat biomass [42] and in several other metal sorption works [43–50]. In the majority of reported cases involving biosorption, pseudo-first-order kinetics are typically applicable to the first stage of the adsorption process, rather than the complete contact time range [51].

In addition to influencing the surface charge and double-layer capacitance of the hydrated particles, salinity can also affect the activities of the adsorbate in solution, which in turn can affect adsorption. Increases in ionic strength typically result in a greater aggregation of suspended particles. The necessity of solute diffusion into interaggregate pores, as a result of increased aggregation, is likely to increase the time dependent partition of sorption. Concurrently, the exterior surface and the rapidly reversible component of sorption both decreases. In this way, sorption might appear to decrease, depending on the reaction time employed [52]. The results obtained shows a contrasting results similar to a previous study [52] and may require more research to understand this contrasting results.

CONCLUSION

In conclusion, the biosorption of the biosorption of lead(II) onto an Antarctic sea-ice bacterial exopolysaccharide was successfully modelled using three models—pseudo-1st, pseudo-2nd and Elovich, and fitted using non-linear regression. Statistical analysis showed that the best kinetic model for adsorption in salt-free water was pseudo-1st order while the best kinetic model for adsorption in seawater was pseudo-2nd order model. All error function analyses also supported these two best models. The kinetic constants values for salt-free water and seawater shows large difference in terms of adsorption in salt-free water and seawater. A higher equilibrium biosorption capacity for lead(II) or q_e values were exhibited for both k_1 and k_2 rate constants in sea water indicating a more efficient adsorption in seawater. In addition, a higher h value indicates a stronger driving force to accelerate the diffusion of adsorbate from solution onto the adsorbent. From these findings, it appears that the sorption mechanism and functional groups involved in saltwater and freshwater environments are fundamentally different.

ACKNOWLEDGEMENT

We thank the Academy of Sciences Malaysia and Sultan Mizan Antarctic Research Foundation for funding the research under the YPASM Smart Partnership Initiative 2020.

REFERENCES

1. Jaishankar M, Tseten T, Anbalagan N, Mathew BB, Beeregowda KN. Toxicity, mechanism and health effects of some heavy metals. *Interdiscip Toxicol.* 2014 ;7(2):60–72.

2. Wani AL, Ara A, Usmani JA. Lead toxicity: a review. *Interdiscip Toxicol.* 2015;8(2):55–64.
3. Prengaman RD, Mirza AH. 20 - Recycling concepts for lead-acid batteries. In: Garche J, Karden E, Moseley PT, Rand DAJ, editors. *Lead-Acid Batteries for Future Automobiles.* Amsterdam: Elsevier; 2017: 575–98.
4. Raviraja A, Vishal Babu GN, Sehgal A, Saper RB, Jayawardene I, Amarasiriwardena CJ, et al. Three cases of lead toxicity associated with consumption of ayurvedic medicines. *Indian J Clin Biochem.* 2010;25(3):326–9.
5. Alissa EM, Ferns GA. Heavy metal poisoning and cardiovascular disease. *J Toxicol.* 2011;870125.
6. Nepalia A, Singh A, Mathur N, Pareek S. Toxicity assessment of popular baby skin care products from Indian market using microbial bioassays and chemical methods. *Int J Environ Sci Technol.* 2018;15(11):2317–24.
7. Gambelunghe A, Sallsten G, Borné Y, Forsgard N, Hedblad B, Nilsson P, et al. Low-level exposure to lead, blood pressure, and hypertension in a population-based cohort. *Environ Res.* 2016;149:157–63.
8. Jarvis P, Fawell J. Lead in drinking water – An ongoing public health concern? *Curr Opin Environ Sci Health.* 2021;20:100239.
9. Chu WL, Phang SM. Biosorption of Heavy Metals and Dyes from Industrial Effluents by Microalgae. In: Alam MdA, Wang Z, editors. *Microalgae Biotechnology for Development of Biofuel and Wastewater Treatment.* Springer, Singapore.
10. Zhang Z, Cai R, Zhang W, Fu Y, Jiao N. A novel exopolysaccharide with metal adsorption capacity produced by a marine bacterium *Alteromonas* sp. JL2810. *Mar Drugs.* 2017;15(6):175
11. Mahapatra B, Dhal NK, Pradhan A, Panda BP. Application of bacterial extracellular polymeric substances for detoxification of heavy metals from contaminated environment: A mini-review. *Mater Today Proc.* 2020;30:283–8.
12. Nagar S, Antony R, Thamban M. Extracellular polymeric substances in Antarctic environments: A review of their ecological roles and impact on glacier biogeochemical cycles. *Polar Sci.* 2021;30:100686.
13. Ma Y, Shen B, Sun R, Zhou W, Zhang Y. Lead(II) biosorption of an Antarctic sea-ice bacterial exopolysaccharide. *Desalination Water Treat.* 2012;42(1–3):202–9.
14. 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.
15. Tran HN, You SJ, Hosseini-Bandegharai A, Chao HP. Mistakes and inconsistencies regarding adsorption of contaminants from aqueous solutions: A critical review. *Water Res.* 2017;120:88–116.
16. Lagergren S. Zurtheorie der sogenannten adsorption gelösterstoffe. *K Sven Vetenskapsakademiens.* 1898;24(4):1–39.
17. Ho YS, McKay G. Pseudo-second order model for sorption processes. *Process Biochem.* 1999;34(5):451–65.
18. Zeldovich J. Über den mechanismus der katalytischen oxydation von CO an MnO₂. *Acta Physicochim URSS.* 1934;1:364–499.
19. Rohatgi A. WebPlotDigitizer. <http://arohatgi.info/WebPlotDigitizer/app/> Accessed; 2015.
20. Halmi MIE, Shukor MS, Johari WLW, Shukor MY. Mathematical modelling of the degradation kinetics of *Bacillus cereus* grown on phenol. *J Environ Bioremediation Toxicol.* 2014;2(1):1–5.
21. Khare KS, Phelan Jr FR. Quantitative comparison of atomistic simulations with experiment for a cross-linked epoxy: A specific volume-cooling rate analysis. *Macromolecules.* 2018;51(2):564–75.
22. Akaike H. New look at the statistical model identification. *IEEE Trans Autom Control.* 1974;AC-19(6):716–23.
23. Burnham KP, Anderson DR. *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach.* Springer Science & Business Media; 2002: 528
24. Kass RE, Raftery AE. Bayes Factors. *J Am Stat Assoc.* 1995;90(430):773–95.
25. Ross T, McMeekin TA. Predictive microbiology. *Int J Food Microbiol.* 1994;23(3–4):241–64.
26. Wang T, Pan X, Ben W, Wang J, Hou P, Qiang Z. Adsorptive removal of antibiotics from water using magnetic ion exchange resin. *J Environ Sci.* 2017;52:111–7.
27. Chu KH, Hashim MA. Adsorption and desorption characteristics of zinc on ash particles derived from oil palm waste. *J Chem Technol Biotechnol.* 2002;77(6):685–93.
28. Gadd GM. Biosorption: critical review of scientific rationale, environmental importance and significance for pollution treatment. *J Chem Technol Biotechnol.* 2009;84(1):13–28.
29. Mu H, Feng X, Chu KH. Calculation of energy flows within complex chemical production systems. *Ecol Eng.* 2012;44:88–93.
30. Wang L, Liu Y, Chu K. A Simplified Model and Similarity Solutions for Interfacial Evolution of Two-Phase Flow in Porous Media. *Transp Porous Media.* 2012;93(3):721–35.
31. González-López ME, Laureano-Anzaldo CM, Pérez-Fonseca AA, Arellano M, Robledo-Ortiz JR. A Critical Overview of Adsorption Models Linearization: Methodological and Statistical Inconsistencies. *Sep Purif Rev.* 2021;0(0):1–15.
32. Qurie M, Khamis M, Manassra A, Ayyad I, Nir S, Scranio L, et al. Removal of Cr(VI) from aqueous environments using micelle-clay adsorption. *Sci World J.* 2013;Article ID 942703:7.
33. Khamizov RKh, Sveshnikova DA, Kucherova AE, Sinyaeva LA. Kinetic model of batch sorption processes: Comparing calculated and experimental data. *Russ J Phys Chem A.* 2018;92:2032–8.
34. Tunali S, Akar T, Özcan AS, Kiran I, Özcan A. Equilibrium and kinetics of biosorption of lead(II) from aqueous solutions by *Cephalosporium aphidicola*. *Sep Purif Technol.* 2006;47(3):105–12.
35. Liu Le, Liu J, Li H, Zhang H, Liu J, Zhang H. Equilibrium, kinetic, and thermodynamic studies of lead (ii) biosorption on sesame leaf. *BioResources.* 2012;7(3):3555–72.
36. Meitei MD, Prasad MNV. Lead (II) and cadmium (II) biosorption on *Spirodela polyrrhiza* (L.) Schleiden biomass. *J Environ Chem Eng.* 2013;1(3):200–7.
37. Samimi M, Shahriari-Moghadam M. Isolation and identification of *Deftia lacustris* Strain-MS3 as a novel and efficient adsorbent for lead biosorption: Kinetics and thermodynamic studies, optimization of operating variables. *Biochem Eng J.* 2021;173:108091.
38. Lee CG, Kim SB. Cr(VI) Adsorption to Magnetic Iron Oxide Nanoparticle-Multi-Walled Carbon Nanotube Adsorbents. *Water Environ Res Res Publ Water Environ Fed.* 2016 Nov 1;88(11):2111–20.
39. Maaloul N, Oulego P, Rendueles M, Ghorbal A, Diaz M. Cu(II) Ions Removal on Functionalized Cellulose Beads from Tunisian Almond (*Prunus dulcis*) Shell. *Environ Sci Eng.* 2021;65–71.
40. Li H, Lin Y, Guan W, Chang J, Xu L, Guo J, et al. Biosorption of Zn(II) by live and dead cells of *Streptomyces ciscaucasicus* strain CCNWHX 72-14. *J Hazard Mater.* 2010;179(1–3):151–9.
41. Mukherjee A, Sarkar S, Parvin R, Bera D, Roy U, Gachhui R. Remarkably high Pb²⁺ binding capacity of a novel, regenerable bioremediator *Papiliotrema laurentii* RY1: Functional in both alkaline and neutral environments. *Ecotoxicol Environ Saf.* 2020;195:110439.
42. Vijayaraghavan K, Rangabhashiyam S, Ashokkumar T, Arockiaraj J. Mono- and multi-component biosorption of lead(II), cadmium(II), copper(II) and nickel(II) ions onto coco-peat biomass. *Sep Sci Technol.* 2016;51(17):2725–33.
43. Periasamy K, Namasivayam C. Removal of copper(II) by adsorption onto peanut hull carbon from water and copper plating industry wastewater. *Chemosphere.* 1996;32(4):769–89.
44. Xie S, Yang J, Chen C, Zhang X, Wang Q, Zhang C. Study on biosorption kinetics and thermodynamics of uranium by *Citrobacter freundii*. *J Environ Radioact.* 2008;99(1):126–33.
45. Nadeem R, Hanif MA, Mahmood A, Jamil MS, Ashraf M. Biosorption of Cu(II) ions from aqueous effluents by blackgram bran (BGB). *J Hazard Mater.* 2009;168(2–3):1622–5.
46. Mahajan G, Sud D. Application of lingo-cellulosic waste material for heavy metal ions removal from aqueous solution. *J Environ Chem Eng.* 2013;1(4):1020–7.
47. Dudu TE, Sahiner M, Alpaslan D, Demirci S, Aktas N. Removal of As(V), Cr(III) and Cr(VI) from aqueous environments by poly(acrylonitril-co-acrylamidopropyl-trimethyl ammonium chloride)-based hydrogels. *J Environ Manage.* 2015;161:243–51.
48. Gunasundari E, Senthil Kumar P. Higher adsorption capacity of *Spirulina platensis* alga for Cr(VI) ions removal: parameter optimisation, equilibrium, kinetic and thermodynamic predictions. *IET Nanobiotechnol.* 2017;11(3):317–28.

49. Gunasundari E, Senthil Kumar P. Adsorption isotherm, kinetics and thermodynamic analysis of Cu(II) ions onto the dried algal biomass (*Spirulina platensis*). *J Ind Eng Chem*. 2017 Dec 25;56:129–44.
50. Sharififard H, Ghorbanpour M, Hosseinirad S. Cadmium removal from wastewater using nano-clay/TiO₂ composite: kinetics, equilibrium and thermodynamic study. *Adv Environ Technol*. 2018 Oct 1;4(4):203–9.
51. Vijayaraghavan K, Yun YS. Bacterial biosorbents and biosorption. *Biotechnol Adv*. 2008 May 1;26(3):266–91.
52. Gonzalez-Davila M, Millero FJ. The adsorption of copper to chitin in seawater. *Geochim Cosmochim Acta*. 1990 Mar 1;54(3):761–8.