INTRODUCTION

Since many decades ago, one of the most significant concerns has been the poisoning of water systems across the world with heavy metals. It is well acknowledged that some metals pose a threat to the health of a variety of different forms of life. The Metals Cr, Cu, Pb, Zn, and Hg stand out as some of the most dangerous pollutants on the list of pollutants that are included in the water framework directive (Directive 2000/60/EC) [1]. Over the course of the past several years, various countries have introduced brand new regulations, tightened existing ones, and increased their level of enforcement regarding wastewater discharges. Organic mercury is a third form of mercury that exists alongside inorganic mercury and elemental mercury that is metallic (methylmercury). These sorts have varying degrees of impact on human organs such as the gastrointestinal tract, the central nervous system, the immune system, the skin, the eyes, and the respiratory system. The amount of mercury released into the environment as a result of human activities, such as the generation of electricity through the processing of industrial waste, the burning of coal, the incineration of waste at homes, and the mining of mercury (along with gold and other metals), has significantly increased [2–8].

Mercury Sorption onto Rice Husk Ash: An Isothermal Remodelling

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ABSTRACT

The rice milling process produces rice husk as a by-product. It is one of the most important agricultural leftovers in terms of volume. The data of the sorption isotherm of Hg (II) (CV) sorption onto rice husk ash, which was plotted using linearized plots of isothermal models were reanalyzed using isothermal models using nonlinear regression. As the datapoints were small, nineteen isotherm models with parameters of only up to three were utilized to prevent overfitting. The models were Henry, Langmuir, Freundlich, Temkin, Dubinin-Radushkevich, Jovanovic, Redlich-Peterson, Sips, Toth, Hill, Khan, BET, Vieth-Sladek, Radke-Prausnitz, Brouers–Sotolongo, Fritz-Schlunder III, Unilan, Fowler-Guggenheim and Moreau. Statistical analysis based on error function analyses such as root-mean-square error (RMSE), adjusted coefficient of determination (adjR²), accuracy factor (AF), bias factor (BF), Bayesian Information Criterion (BIC), corrected AICc (Akaike Information Criterion), and Haman-Quinn Criterion (HQC) showed that Freundlich model was the best model. The value of the maximum monolayer adsorption capacity for Hg binding to rice husk ash according to the Langmuir’s parameter q max was 3.998 mg g⁻¹ (95% Confidence interval from 2.473 to 5.523), while b L⁻¹ (L mg⁻¹), the Langmuir model constants was 0.067 L mg⁻¹ (95% C.I. from 0.001 to 0.134). The Freundlich model is unable to forecast the maximal adsorption capacity. The Halsey rearrangement of the Freundlich equation gave the estimated maximum absorption of 3.39 mg g⁻¹, which is very close to the experimental value. The nonlinear regression method provides parameter values within the 95% confidence interval, facilitating improved comparability with prior research.

KEYWORDS

Mercury, Rice Husk, Remodelling, Isotherms, Freundlich
the ingestion of fish and shellfish that have been polluted. Mercury is not removed from the body by cooking it [2,3,5,9–12].

Treatment centers are currently using some of the novel and much improved approaches that have been developed in response to this issue. Several different treatment processes have been proposed as possible solutions for eliminating heavy metals from water sources in the existing literature. Among the techniques that fit this description are coagulation, chemical precipitation, evaporation, electrolysis, adsorption, and reverse osmosis. On the other hand, these conventional forms of technology may be insufficient, too costly, or even cause new problems. It’s effective and cost-efficient, and it’s easy to execute. Therefore, adsorption is likely to be the most popular approach. Future progress may be hampered, however, by the cost of the adsorbent and the energy needed to keep it refilled.

Biosorption, a risk-free and cost-effective method for cleaning polluted water, is widely adopted for this purpose. Biosorbents can be made from either biomass or natural substrates. There has been a lot of research on the topic of mercury biosorption published in recent years [13–23]. The quality of this study is exceptional, and it was not conducted at an unreasonably high expense. Adsorbents with cheap costs include those that are plentiful in nature or created as a byproduct of industrial processes, and those that may be acquired in vast numbers with little to no additional expense. There has been a rise in interest in employing inexpensive materials for absorbent applications, which is in line with the growing importance of the issue of recycling garbage and similar resources.

This is becoming increasingly important in many fields, including adsorptive materials where there is a rising need and desire for more cost-effective solutions. Because rice husk can be burnt to generate steam, many different types of enterprises may save money by cutting back on their usage of both energy and raw materials. Ash from boilers and furnaces that burn rice husks is known as rice husk ash. This ash is collected in a dust collector located upstream from the stacks. Ash remaining after burning rice husks is sometimes called “rice husk ash.” Adsorbents like rice husk ash may be used as an unreasonably high expense. Adsorbents with cheap costs include those that are plentiful in nature or created as a byproduct of industrial processes, and those that may be acquired in vast numbers with little to no additional expense. There has been a rise in interest in employing inexpensive materials for absorbent applications, which is in line with the growing importance of the issue of recycling garbage and similar resources.

The accurate assignment of the kinetics and isotherms of biosorption is an absolutely necessary step in gaining an understanding of the biosorption process in these particular species. In many cases, the published research will provide a linearized form of an obviously nonlinear curve that these data produce. The error structure of the data is affected when nonlinear data is linearized, which makes it more difficult to assess uncertainty, which is often expressed as a confidence range of 95 percent. The purpose of this study is to rework a previously published study on the sorption of zinc on rice husk ash [29], which utilize linear regression to obtain best fitting models.

METHOD

Data acquisition and fitting

Figure 2 data from a previously published study [29] was digitized using the freeware Webplotdigitizer 2.5 [30]. After that, the data were nonlinearly regressed using the curve-fitting program Curve-Expert Professional (Version 2.6.5, Copyrights 2011-2017, Daniel G. Hyams). Digitization using this program has been praised for its dependability [31,32].

Isotherms

As the value of the datapoints is very small, only models having parameters of up to three were considered to prevent overfitting. Nineteen models were tested.

Table 1. Mathematical models that were used in modelling data [33,34].

<table>
<thead>
<tr>
<th>Isotherm</th>
<th>Mathematical model</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Henry’s law</td>
<td>( q_e = \frac{Hq_m C_e}{1 + b C_e} )</td>
<td>[35]</td>
</tr>
<tr>
<td>Langmuir</td>
<td>( q_e = \frac{q_max (1 - e^{-b C_e})}{1 + b C_e} )</td>
<td>[36]</td>
</tr>
<tr>
<td>Freundlich</td>
<td>( q_e = K F C_e^{1/n} )</td>
<td>[37]</td>
</tr>
<tr>
<td>Dubinin-Radushkevich</td>
<td>( q_e = q_{max} e^{-K_e [RT/(1 + b C_e)]} )</td>
<td>[38,39]</td>
</tr>
<tr>
<td>Temkin</td>
<td>( q_e = \frac{RQ}{B}(\ln(a e C_e)) )</td>
<td>[40,41]</td>
</tr>
<tr>
<td>Redlich-Peterson</td>
<td>( q_e = \frac{K R C_e}{(1 + \beta C_e)^{1/\beta}} )</td>
<td>[42]</td>
</tr>
<tr>
<td>Sips</td>
<td>( q_e = \frac{K S C_e^{1/\alpha}}{1 + K S C_e^{1/\alpha}} )</td>
<td>[43]</td>
</tr>
<tr>
<td>Toth</td>
<td>( q_e = \frac{q_{max}}{1 + e^{-K T C_e}} )</td>
<td>[44]</td>
</tr>
<tr>
<td>Hill</td>
<td>( q_e = \frac{q_{max} C_e^{n}}{1 + C_e^{n}} )</td>
<td>[45]</td>
</tr>
<tr>
<td>Khan</td>
<td>( q_e = \frac{q_{max} C_e^{n}}{1 + C_e^{n}} )</td>
<td>[46]</td>
</tr>
<tr>
<td>BET</td>
<td>( q_e = \left(1 - \beta_{app} C_e\right)\left(1 - \beta_{app} C_e + \alpha_{app} C_e\right) )</td>
<td>[47]</td>
</tr>
<tr>
<td>Vieth-Sladke</td>
<td>( q_e = \frac{q_{max} C_e^{n}}{1 + K S C_e^{n}} )</td>
<td>[48]</td>
</tr>
<tr>
<td>Radke-Prausnitz</td>
<td>( q_e = \frac{q_{max}}{1 + K C_e^{n}} )</td>
<td>[49]</td>
</tr>
<tr>
<td>Brouers-Sotolongo</td>
<td>( q_e = q_{max}\left(1 - \exp \left(-K_{exp} C_e^{n}\right) \right) )</td>
<td>[50]</td>
</tr>
<tr>
<td>Fritz-Schindler-III</td>
<td>( q_e = \frac{q_{max} C_e^{n}}{1 + K C_e^{n}} )</td>
<td>[51]</td>
</tr>
<tr>
<td>Fowler-Guggenheim*</td>
<td>( q_e = \frac{K G C_e^{n}}{1 + K G C_e^{n}} )</td>
<td>[52]</td>
</tr>
<tr>
<td>Moreau</td>
<td>( q_e = q_{max} \sqrt{1 + K C_e^{n}} )</td>
<td>[53]</td>
</tr>
<tr>
<td>Unilan</td>
<td>( q_e = q_{max} \ln \left(a e C_e + b C_e + c e^{d C_e}\right) )</td>
<td>[54]</td>
</tr>
</tbody>
</table>

Note *Implicit equation or function.

Statistical analysis

A set of statistical discriminatory tests 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 (R²) were used in this study. The RMSE was computed using Equation 1, and it stands to reason that the fewer parameters utilized, the smaller the RMSE will be. n is for the total number of observations made in the experiment, Obi and Pdi stand for the total number of observations made in the experiment and projections, and p stands for the total number of parameters [54].

\[
RMSE = \sqrt{\frac{\sum_{n=1}^{p}(P_{pdi}-O_{obi})^2}{n-p}} \quad (\text{Eqn. 1})
\]

The modified R² is used to get around the fact that R², also known as the coefficient of determination, does not take into account the number of parameters in a model. In the equation, \( S_y^2 \) represents the total variance of the y-variable.\( (\text{Equations 2 and 3}) \), while RMS is the Residual Mean Square.
Bias factor = 10 \left( \sum_{i=1}^{n} \log \left( \frac{P_{d}/O_{b}}{n} \right) \right) \quad \text{(Eqn. 2)}

Accuracy factor = 10 \left( \sum_{i=1}^{n} \log \left( \frac{P_{d}/O_{b}}{n} \right) \right) \quad \text{(Eqn. 3)}

In Equation 4, the AICc is calculated as, where \( p \) is the total number of parameters and \( n \) is the total number of observations. When dealing with data that has many parameters but few values, the corrected Akaike information criterion (AICc) is applied. \[55\]. A model with a lower AICc score is considered more likely to be right \[55\]. It finds a favorable medium between a model's simplicity and its accuracy \[56\].

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

The Bayesian Information Criterion (BIC) is another information-theory-based statistical tool (BIC) (Equation 5). The number of parameters receives a harsher penalty from this error function than it does from the AIC \[30\].

\[
BIC = n\ln \left( \frac{RSS}{n} \right) + k\ln(n) \quad \text{(Eqn. 5)}
\]

Another method for analyzing error functions that is grounded in information theory is called the Hannan-Quinn information criterion (HQC) (Equation 6). Because of the \( \ln \ln n \) element in the calculation, the HQC is more consistent than the AIC \[55\].

\[
HQC = n\ln \left( \frac{RSS}{n} \right) + 2k\ln(\ln n) \quad \text{(Eqn. 6)}
\]

Two more error function analyses that were derived from Ross's work are referred to as the Accuracy Factor (AF) and the Bias Factor (BF) \[55\]. These error functions do statistical evaluations of models to see how well they fit data, but they do not punish models based on the number of parameters (Equations 7 and 8).

\[
\text{Adjusted } (R^2) = 1 - \frac{RSS}{\hat{\sigma}^2} \quad \text{(Eqn. 4)}
\]

\[
\text{Adjusted } (R^2) = 1 - \frac{(1-R^2)(n-1)}{(n-p-1)} \quad \text{(Eqn. 5)}
\]

RESULTS AND DISCUSSION

The equilibrium data from \[57\] was analyzed making use of the models—Henry, Langmuir, Freundlich, Redlich-Peterson, Sips, BET, Toth, Hill, Khan, Vieth-Sladek, Radke-Prausnitz, Unilan, Fritz-Schlunder III, Fritz-Schlunder IV, and Fritz-Schlunder V, were employed in determining the best fit by making use of non-linear regression. Henry, Langmuir, Hill, Vieth-Sladek, Unilan, Sips, and BET do not match well with the data, however Freundlich, Redlich-Peterson, Toth, Khan, Radke-Prausnitz, Fritz-Schlunder III, Fritz-Schlunder IV, and Fritz-Schlunder V did fit well with the data. Henry, Langmuir, Hill, Vieth-Sladek, Unilan, Sips, and BET do not match well with the data, however Freundlich, Redlich-Peterson, Toth, Khan, Radke-Prausnitz, Fritz-Schlunder III, Fritz-Schlunder IV, and Fritz-Schlunder V did fit well with the data. Henry, Langmuir, Hill, Vieth-Sladek, Unilan, Sips (Figs. 1 – 19).

We discovered that the Freundlich isotherm model had the best combination of low values for AICc, BIC, HQC, and RMSE, as well as values of AF, BF, and \( \text{adjR}^2 \) that were closest to unity. This made the Freundlich isotherm model the model with the best overall fit. As a result of this, it was the most accurate model for describing isotherms. Following this is the Langmuir model, which is followed by the Jovanovic model, which is followed by the Fritz-Schlunder III model, and then lastly the Toth model (Table 2). It discusses and supports the greater accuracy of employing nonlinear regression as opposed to the linear regression employed in the original study, which suggests the 2-parameter Jovanovic isotherm as the best model because enough models fitted well with the burned rice husk data.
Fig. 4. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Temkin isotherm model.

Fig. 5. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Dubinin-Radushkevich isotherm model.

Fig. 6. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Jovanovic isotherm model.

Fig. 7. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Redlich-Peterson isotherm model.

Fig. 8. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Sips isotherm model.

Fig. 9. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Toth isotherm model.
Fig. 10. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Hill isotherm model.

Fig. 11. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Khan isotherm model.

Fig. 12. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the BET isotherm model.

Fig. 13. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Vieth-Sladek isotherm model.

Fig. 14. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Radke-Prausnitz isotherm model.

Fig. 15. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Brouers-Sotolongo isotherm model.
Fig. 16. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Fritz-Schlunder III isotherm model.

Fig. 17. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Unilan isotherm model.

Fig. 18. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Fowler Guggenheim isotherm model.

Fig. 19. Adsorption isotherm of Hg (II) onto rice husk ash as modelled using the Moreau isotherm model.

Table 2. Error function analysis for the fitting of the isotherm of Hg (II) onto rice husk ash.

<table>
<thead>
<tr>
<th>Model</th>
<th>p</th>
<th>RMSE</th>
<th>adR²</th>
<th>AICc</th>
<th>BIC</th>
<th>HQC</th>
<th>BF</th>
<th>AF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Henry</td>
<td>1</td>
<td>0.80</td>
<td>0.64</td>
<td>6.30</td>
<td>6.30</td>
<td>-1.91</td>
<td>0.49</td>
<td>2.17</td>
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<tr>
<td>Langmuir</td>
<td>2</td>
<td>0.22</td>
<td>0.96</td>
<td>1.48</td>
<td>1.48</td>
<td>-1.94</td>
<td>0.90</td>
<td>1.16</td>
</tr>
<tr>
<td>Freundlich</td>
<td>2</td>
<td>0.13</td>
<td>0.98</td>
<td>-5.25</td>
<td>-5.25</td>
<td>-23.66</td>
<td>1.04</td>
<td>1.06</td>
</tr>
<tr>
<td>Temkin</td>
<td>2</td>
<td>0.22</td>
<td>0.96</td>
<td>1.48</td>
<td>1.48</td>
<td>-16.94</td>
<td>0.90</td>
<td>1.16</td>
</tr>
<tr>
<td>Dubinin</td>
<td>2</td>
<td>1.42</td>
<td>-15.89</td>
<td>23.77</td>
<td>23.77</td>
<td>5.35</td>
<td>0.63</td>
<td>1.64</td>
</tr>
<tr>
<td>Jovano</td>
<td>2</td>
<td>0.28</td>
<td>0.93</td>
<td>4.36</td>
<td>4.36</td>
<td>-14.05</td>
<td>0.85</td>
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<td>Red-Pet</td>
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<td>0.14</td>
<td>0.98</td>
<td>26.08</td>
<td>26.08</td>
<td>-22.54</td>
<td>0.97</td>
<td>1.07</td>
</tr>
<tr>
<td>Sips</td>
<td>3</td>
<td>0.14</td>
<td>0.98</td>
<td>26.21</td>
<td>26.21</td>
<td>-22.42</td>
<td>0.95</td>
<td>1.07</td>
</tr>
<tr>
<td>Toth</td>
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<td>0.08</td>
<td>0.99</td>
<td>19.94</td>
<td>19.94</td>
<td>-28.68</td>
<td>0.98</td>
<td>1.04</td>
</tr>
<tr>
<td>Hill</td>
<td>3</td>
<td>0.14</td>
<td>0.98</td>
<td>26.30</td>
<td>26.30</td>
<td>-22.32</td>
<td>0.96</td>
<td>1.07</td>
</tr>
<tr>
<td>Khan</td>
<td>3</td>
<td>0.14</td>
<td>0.98</td>
<td>26.13</td>
<td>26.13</td>
<td>-22.49</td>
<td>1.00</td>
<td>1.05</td>
</tr>
<tr>
<td>BET</td>
<td>3</td>
<td>0.15</td>
<td>0.98</td>
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<td>27.32</td>
<td>-21.31</td>
<td>0.98</td>
<td>1.07</td>
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<tr>
<td>Vieth-S</td>
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<td>0.15</td>
<td>0.98</td>
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<td>-21.42</td>
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<tr>
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<td>25.06</td>
<td>-23.57</td>
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<tr>
<td>Brouers-Sotolongo</td>
<td>3</td>
<td>1.71</td>
<td>-25.60</td>
<td>56.25</td>
<td>56.25</td>
<td>7.63</td>
<td>0.48</td>
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<td>Fritz-Schlunder III</td>
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<td>0.06</td>
<td>1.00</td>
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<td>0.17</td>
<td>0.97</td>
<td>28.56</td>
<td>28.56</td>
<td>-20.06</td>
<td>0.96</td>
<td>1.09</td>
</tr>
<tr>
<td>Fowler-Guggenheim</td>
<td>3</td>
<td>0.37</td>
<td>0.83</td>
<td>38.03</td>
<td>38.03</td>
<td>-10.59</td>
<td>0.92</td>
<td>0.92</td>
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<tr>
<td>Moreau</td>
<td>3</td>
<td>0.18</td>
<td>0.97</td>
<td>29.00</td>
<td>29.00</td>
<td>-19.62</td>
<td>1.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Note: RMSE Root mean Square Error  
adR² Adjusted Coefficient of determination  
p no-of parameters  
AF Accuracy factor  
BF Bias factor  
BIC Bayesian Information Criterion  
AICc Adjusted Akaike Information Criterion  
HQC Hannan-Quinn information criterion

Langmuir isotherm

There are many different models of isotherms, the most well-known of which is the Langmuir isotherm, which being entirely mechanical. The model assumed that adsorbate would be uniformly adsorbed onto the adsorbent. The isotherm works under the assumption that the structure of the adsorbent is consistent throughout, as well as that the energy of each adsorption site is the same [58]. Due to the exponential decrease in intermolecular interactions with increasing distance, this isotherm model predicts the appearance of monolayer coverage of the adsorbent at the adsorbent's outer surface. This is the result of the adsorbent's growing distance from the solute. This model additionally streamlines the linear connection and makes the prediction of a constant capacity for adsorption by a monolayer.
On the basis of this, it is believed that Henry's model will be accurate for solutions ranging from those that are extremely diluted to those that are exceedingly concentrated [59]. In sorption research, including Zn sorption research, two of the models that are employed most frequently are the Langmuir model and the Freundlich model. The non-linear regression technique predicted a maximum adsorption parameter and model constant that were almost equal to those found in the original investigation; nevertheless, it was unable to create a confidence range for the projected values that contained 95% of the true value.

**Freundlich isotherm**

A well-known example of an empirical model for adsorption and desorption is the Freundlich equation, which was initially devised for the gas phase. In a Freundlich adsorption isotherm, the adsorbate forms a monomolecular layer on the surface of the adsorbent. The Freundlich equation offers some relevant empirical data on particle sorption; but, after a certain concentration, it changes its behavior and becomes nonlinear; as a result, its applicability is restricted [60–62]. In contrast to the Langmuir isotherm, the Freundlich model can be extended in order to take into account adsorption that occurs across many layers.

The results of this isotherm model suggest that the heat of adsorption and the affinities of molecules that have been adsorbed might be unevenly distributed across a surface that is composed of different types of matter. The exponential distribution of active sites, in addition to the energy and surface heterogeneity, are both defined by the statement that makes up the Freundlich isotherm model. The Freundlich isotherm model was initially used in the attempt to characterize the steps of adsorption of adsorbate onto the adsorbent charcoal. This was done in an attempt to determine how well the process worked. There was an alteration in the mass ratio of the adsorbate that was coupled to the adsorbent whenever there was an increase in the concentration of the solution.

This leads one to the conclusion that the total amount of adsorption which takes place at each location is equal to the quantity that is adsorbed. After the most stable binding sites are fully occupied, the amount of energy that is needed for adsorption begins to decrease at a pace that is exponential in nature [59,63,64]. Additionally, the Freundlich model was the most accurate representation of lead(II) sorption by a modified Jordanian zeolite [65], *Chlorococcum aquaticum* biomass [66], by a Guar gum/bentonite bionanocomposite [67], the sorption of other metal and radionuclides [68–73] and nanoparticle adsorbents of cellulose origin [74].

The Freundlich model, due to the empirical character of its data, is unable to make accurate predictions regarding the maximal adsorption capacity at which \( K_F \) (mg g\(^{-1}\)L mg\(^{-1}\))^1/n\( F \)) is the Freundlich isotherm constant, and \( n_F \) is the Freundlich exponent. A small 1/n\( F \) value indicates a heterogenous system [60,75]. Due to the inability of the Freundlich equation to predict maximal adsorption, the Halsey restructuring of the Freundlich equation was developed [76] (Equation 6) gave the estimated maximum absorption of 3.39 mg g\(^{-1}\), which is very close to the experimental value.

\[
K_F = \frac{q_m F}{C_e^{1/n_F}} \quad \text{(Eqn. 6)}
\]

**Temkin isotherm**

In the Temkin isothermal model, which was developed by Temkin and Pyznar, adsorption is described as a constant function of temperature until it reaches its maximum binding energy [40]. Because of indirect adsorbate-adsorbate interactions over the surface of the heterogeneous material, the amount of surface coverage causes a drop in the heat of adsorption that is linearly proportional to the amount of surface coverage. The Temkin isotherm is constructed with the adsorption isotherm developed by Langmuir as its foundation. The positive heat produced by adsorption demonstrates that adsorption is an exothermic process \((\Delta H < 0)\). The widely used Temkin model that is shown below is faulty as a result of a disparity in the dimensions between the left side of the equation and the right side of the equation;

\[
q_e = \frac{RT}{\beta T} \ln (K_T C_e) \quad \text{(Eqn. 33)}
\]

The accurate application of the Temkin model, which Chu has just brought to light and improved, is summarized in the following [41];

\[
\frac{q_e}{q_{mT}} = \frac{RT}{\beta T} \ln (K_T C_e) \quad \text{(Eqn. 34)}
\]

Where, in this equation, \( K_T \) is the adsorption equilibrium constant of the solute on the solid surface expressed as L mg\(^{-1}\), solute equilibrium concentration \( C_e \) is mg L\(^{-1}\), \( q_e \) and \( q_{mT} \) are the equilibrium and saturated adsorption amount and expressed as mg g\(^{-1}\), while \( \beta T \) has a unit of J mol\(^{-1}\) and represents the adsorption heat parameter. The 3-parameter Temkin model has issue of having a large 95% confidence interval, and is probably due to the parameters being intertwined [41] and having a dependency near to unity [54,77].

**Jovanovic isotherm**

An adsorption surface presupposition is taken into account by the Jovanovic isotherm, which is quite comparable to the Langmuir isotherm’s. This scenario relates to a second estimate for localized monolayer adsorption when there are no lateral interactions present. The surface binding vibrations of an adsorbed species are taken into consideration in this model, which is the primary distinction between it and the Langmuir model [36] (Table 3). The isotherm also takes into account the surface binding vibrations of the adsorbed species. The Jovanovic isotherm, which encompasses three parameters, is an alternative model that takes into account the phenomenon of multilayer adsorption [36].

**Table 3. Isothermal models’ constants.**

<table>
<thead>
<tr>
<th>Model</th>
<th>Unit</th>
<th>Value</th>
<th>(95% confidence interval)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Freundlich</td>
<td>( K_F ) (mg g(^{-1})L mg(^{-1}))^1/n( F ))</td>
<td>0.62</td>
<td>0.548 to 0.692</td>
</tr>
<tr>
<td></td>
<td>( q_{mT} ) mg g(^{-1})</td>
<td>2.468</td>
<td>2.270 to 2.667</td>
</tr>
<tr>
<td></td>
<td>( q_{mT} ) mg g(^{-1})</td>
<td>3.39</td>
<td></td>
</tr>
<tr>
<td>Temkin(1)</td>
<td>( q_{mT} ) mg g(^{-1})</td>
<td>0.848</td>
<td>Too large</td>
</tr>
<tr>
<td></td>
<td>( b_T ) L mg(^{-1})</td>
<td>1.287</td>
<td>-1.624 to 4.197</td>
</tr>
<tr>
<td></td>
<td>( b_T ) J mol(^{-1})</td>
<td>3.011</td>
<td>Too large</td>
</tr>
<tr>
<td>Langmuir</td>
<td>( q_{mT} ) mg g(^{-1})</td>
<td>3.988</td>
<td>2.473 to 5.523</td>
</tr>
<tr>
<td></td>
<td>( b_T ) L mg(^{-1})</td>
<td>0.067</td>
<td>0.001 to 0.134</td>
</tr>
<tr>
<td>Jovanovic</td>
<td>( q_{mT} ) mg g(^{-1})</td>
<td>3.307</td>
<td>2.152 to 4.462</td>
</tr>
<tr>
<td></td>
<td>( K_F ) dimensionless</td>
<td>0.061</td>
<td>0.008 to 0.114</td>
</tr>
</tbody>
</table>

Notes:
- \(1\) Isotherm with \( \beta \) term should not be plotted using data that starts from the origin (0,0)
- \(2\) Isotherms having an RT term should be plotted using the temperature (Kelvin) studied
- \(3\) Isotherms that have no direct way in estimating the maximum adsorption capacity (mg g\(^{-1}\))
The removal of metals and dyes from wastewater is possible through the use of a wide variety of sorbents that have been created through coating, chemical synthesis, and various other processes [46–51]. The process of grinding of rice results in the production of a waste product known as rice husk. It is one of the most important agricultural byproducts in terms of the total volume that it produces [78,79]. According to estimates, developing nations would generate 500 million tons of rice annually, with an additional 100 million tons of rice husk that may be used. In the past, rice husks were historically utilized by the rice industry to produce blocks that are used as panels in civil construction, in addition to serving as an energy source for boilers [79,80]. However, there are a great deal more rice husks than are needed for local uses, which creates disposal issues. This material was chosen because it does not need regeneration, has a granular structure, is chemically stable, and can be produced cheaply.

CONCLUSION

Non-linear regression has been used to fit several models with one to three parameters to the data on the adsorption isotherms of Hg (II) dye onto rice husk ash. Multiple tests using a variety of metrics—including root-mean-square error (RMSE), adjusted coefficient of determination (adjR2), bias factor (BF), accuracy factor (AF), bias information coefficient (BIC), and corrected Akaike Information Criterion (AICC)—all pointed to the Freundlich model as the best option. Since the Freundlich model is based on empirical data, it cannot predict the maximum adsorption capacity. Maximum absorption was estimated to be 3.39 mg g⁻¹ using the Halsey reorganization of the Freundlich equation, which is extremely comparable to the experimental measurement. Parameter values in the 95% confidence interval region are shown in the nonlinear regression method, facilitating comparison with previous research.

REFERENCE


