Maximization of Cr Removal in Continuous Counter-current Liquid-Solid Fluidized Bed: A Machine Learning Approach

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Abstract. Continuous counter-current liquid solid (CCLS) fluidized bed is used as an adsorption column. Due to the counter current contacting pattern and easiness in handling the fresh as well as used adsorbent continuously, CCLS adsorption column can be preferred over packed adsorption column. In the present work experimental data for chromium removal from the wastewater using CCLS adsorption has been used for developing models using artificial neural network (ANN), a well-known machine learning technique. The percentage removal of Cr is mapped as function of liquid velocity, solid velocity, particle diameter, initial concentration, and height of the column through ANN. The developed ANN model is used as objective function for the design of the process using genetic algorithm (GA), a metaheuristic tool for optimization. The results provide specific guidelines for achieving optimum Cr removal.

Keywords: Counter Current Liquid Solid Fluidized Bed, Percentage Cr removal, Optimization, Artificial Neural Network, Genetic Algorithm.

1. INTRODUCTION

Water is very important to humans and all living things. Different technologies help to achieve related water resource goals [1]. Water treatment is any approach to improving water quality to make it more acceptable for specific uses, like drinking water, industrial water supply, irrigation etc. Water treatment removes contaminated and undesirable parts, or reduces their concentration, making water ideal for use. Water treatment can be used for many procedures, such as purification and disinfection [2].

Metals are incorporated into water systems as a result of various human activities, volcanic eruptions, metals and/or metal contamination. Arsenic, nickel, copper, chromium, cadmium, and lead are heavy metal pollutants [3]. Some metals, such as zinc, iron and lead, are essential for aquatic life and human life. Chronic exposure to heavy metals can have serious health consequences in the long run [4]. The Environmental Protection Agency (EPA) advises the highest permissible concentration of natural water metals for the safety of public health [5]. Among the heavy metals the chromium removal process is designed in this work. Pure Cr and most Cr compounds are insoluble in water and the only soluble Cr compounds are chromium oxide and chromium chloride. Daily consumption of Cr is strongly dependent on the feed level, which is usually 15-200μg, but up to 1 mg [6]. Hexavalent Chromium is renowned for its safety, impacts on the atmosphere and extreme toxicity. Health
outcomes associated with hexavalent Cr exposure include diarrhea, bleeding in the stomach and intestines, constipation, liver, and kidney failure [7].

As demand for water purification grows, there is always the need to find a more efficient and economical approach to water treatment. Current water treatment technologies include mechanical therapy, hydrothera, and land treatment [8]. Heavy metals (chromium in our case) can be removed from wastewater using various methods. Some of them are aquatic and terrestrial biomass, membrane processes, absorption, and the use of carbon nanotubes [9]. Many trees and different terrestrial biomasses are used for bioremediation which can remove many heavy metals [10].

Adsorption can be a great alternative for dye-containing medicines from the textile and paper industries. One of the most effective topical methods for dyeing this waste is absorption, which can be extended to different types of sorbent kits such as half-bed and full-bed batch mode. The most effective way to eliminate pollution is through fluidization. Continuous operation is either current or temporary. CCLS system are used as free-standing or controlled systems. It manages the benefits of a standard fixed bed and rewards the benefits of a calculated flow. In CCLS system, the liquid is pumped from the bottom via a pump into the test section while the solid is discharged from the above. The flow rate of liquid is maintained for different flowrates while the solid particle size is maintained constant by passing it through a scale. The mass transfer happens when a solid particle meets the liquid particle-containing solute in the test section [11]. The flow rate is maintained in such a way that the flooding should not happen, and the solid particle retains inside the test section due to drag force until the experiment is finished. Since the experiment is continuous, the liquid is pumped continuously and solid is discharged continuously from the bottom. This adds additional benefit over conventional CCLS system as a greater number of experiments can be done and the working cycle can be increased.

K. Nagarajan et al. describe the experimental and modeling study of the CCLS system [12]. It uses a one-dimensional two-fluid model to approximate the impact on the annular drop in pressure and holdup of various heterogeneous variables. Nowadays, data-driven models using machine learning, e.g., artificial neural network (ANN) [13], have shown capability for mapping complex systems. For optimization of the parameters of complex systems, metaheuristic algorithms, e.g., genetic algorithm (GA) [14] can be effective. For past several years, chemical engineers all over the world have adopted new techniques and tools thus include data science in their work and research [15]. Machine learning has been used to optimize several chemical processes. Multi Objective optimization is being used to optimize process cost, reaction yield, impurity levels etc. Pharmaceuticals industry have been widely using this optimization process to optimize impurity profiles [16]. Hong Guo et al. used ANN models to predict effluent concentration from wastewater [17]. They used daily water quality data to evaluate the performance of the ANN models based on various criteria. Prabhu et al. used ANN to model hydrodynamics parameters in a counter flow inverse fluidized bed reactor [18]. The effect of various operating variables was assessed on liquid holdup, gas holdup etc. This was used to train the feed forward multilayer perceptron ANN. Operating conditions were optimized using GA. Yasin et al. developed an environment friendly cardiovascular system to remove lead ions from aqueous solutions [19]. They used ANN to develop a model to predict the percentage of lead ion removal. These models were further used for GA to optimize the percentage removal of lead ions from aqueous solutions. Mazumder et al. used GA in Liquid Solid Circulating Fluidized Bed system for continuous protein recovery. The optimal solutions were used to improve the performance of the system by helping to adjust the operating conditions [20].

In the present work, the percentage removal of Cr in a CCLS system are modelled by ANN using experimental data. The models have liquid velocity, solid velocity, particle diameter, initial concentration, and height of the column as the input parameters. The developed ANN model is used as objective functions for the design of the process using GA.

2. METHODOLOGY
2.1. Problem Formulation
The CCLSS parameters are optimized for percentage removal of Cr. ANN has been used to develop model for finding a relation between the input and the output variables. The ANN model has been used as objective function to find out the optimum solutions using GA for the above-mentioned studies.

2.2. Database

A set of 110 numbers of data are collected for percentage removal study, from a standard source [11]. Table 1 shows the ranges of input variables, output variables, means and standard deviations.

| Input Variables     | Minimum | Maximum | Mean  | Standard Deviation |
|---------------------|---------|---------|-------|--------------------|
| Particle dia        | 0.5     | 1       | 0.833 | 0.237              |
| Height of Column    | 0       | 150     | 73.2  | 58.844             |
| Solid Vel.          | 0.262   | 0.89    | 0.475 | 0.23               |
| Liq. Vel.           | 0       | 0.708   | 0.362 | 0.285              |
| Initial conc.       | 100     | 200     | 191.67| 25.117             |

| Output Variables    | Minimum | Maximum | Mean  | Standard Deviation |
|---------------------|---------|---------|-------|--------------------|
| % removal           | 0       | 92.584  | 50.814| 32.676             |

2.3. Computational Procedure

2.3.1. Artificial Neural Network (ANN) Modelling

An Artificial Neural Network (ANN) is a paradigm for data processing that mimics the human's nervous structure while transferring knowledge to the brain. It consists of many interlinked sections called neurons, which operate effectively with each other to rectify particular issues. For testing, ANN is programmed utilizing a particular issue, such as information processing, data interpretation, or learning approach. Every neural network has certain processing elements which receives signals from the outside world, called the set of input units or the given set of input nodes. There are one or more hidden networks for processing data which only obtain feedback from other processing units. A collection of processing units is the outcome of a simulation on a neural network. ANN uses a radically new strategy to the usage of techniques of content analysis and regulation of the material systems to adjust data or mathematical approaches. ANN's fundamental benefit is that it doesn't take any statistical model into account; ANN observes from a variety of incoming and outgoing values without recognizing behavior, perceptions, and experiences.

2.3.2. Sensitivity Analysis

For designing a new model, it is important to understand the relative influence of input variables on output. But it is difficult to understand the influence in ANN models due to the complex relations generated. Sensitivity analysis is done using the saved synaptic weights of the trained ANN models using the method mentioned elsewhere [21].

2.3.3. Genetic Algorithm

Genetic Algorithm originates from biological evolution and heavily inspired by natural selection theory of Darwin. It is a computing tool used to find a true solution or an estimated one. This algorithm utilizes natural biologically based mechanisms such as mutation, crossover, inheritance, and selection. The methodology begins with a series of solutions created arbitrarily (known as the first generation) based on a blind search for optimum solutions [22-24]. The solutions are generated using a set of computer programs. Each of the solutions is treated as an individual. The fitness of each of the individuals is evaluated based on to what extent the solution achieves the target property. The programmer gives the assessment feature and offers the entities a score depending upon how they meet the intended outcome [25, 26]. The right candidates are selected according to their ratings. The best-fitted solutions undergo crossover and mutation to form the next solution set (the 2\textsuperscript{nd} generation). Better individuals (or parents) are chosen so that they generate better offspring in the next generation. This
process of selection of best-fitted solutions and formations of new generations occur until it reaches a particular number of generations or a satisfactory fitness level.

3. RESULT AND DISCUSSION

The percentage removal of chromium with water is modelled using ANN and particle diameter, height of the column, solid and liquid velocity, and initial concentration of chromium ($C_0$) in water are considered as the input variables. The neural network model has 4 hidden neurons in the only hidden layer and was trained using the Levenberg-Marquardt backpropagation algorithm. The prediction regression plot of the model is given as Fig. 1(a). Fig. 1(b) displays results of sensitivity analysis and it shows that the particle diameter has a negative effect and the column height, initial concentration of chromium, solid and liquid velocity have a positive effect.

![Fig. 1: The ANN model for percentage removal showing (a) prediction regression plot and (b) sensitivity analysis](image)

The simulation results of the model are shown as surface plots in Fig 2. Fig. 2(a) shows the variation of %removal of Cr with variation of particle diameter and height of the column. The figure clearly depicts that the Cr removal increases significantly with increase in column height, whereas decreases by a small amount at higher particle diameter. This also corroborates the findings of the sensitivity analysis, shown in Fig. 1(b). When solid velocity and column height are varied simultaneously (Fig. 2(b)), it shows that the effect of solid velocity is less significant. The Cr removal increases a bit with increase in solid velocity, particularly for higher column height. It is also found that if initial concentration is high, the percentage removal of Cr is also high (Fig. 2(c)).
Genetic Algorithm is employed to maximize the removal of chromium from water. For this maximization process, the initial concentration of chromium in water is fixed at 200 ppm and the lower limit of liquid velocity is kept at 0.1 cm/s to avoid complete stagnation. The upper limit of the column height is varied between 150 to 200 cm to find different solutions. Fig. 3(a) shows that the percentage removal increases with increase in height of the column as expected. It is interesting to note that the optimum (preferred) solid velocity decreases with increase in column height (Fig. 4). This phenomenon needs to be studied further to get better understanding of the system.
4. CONCLUSION
Artificial Neural Network is used to develop model percentage removal of chromium. The sensitivity analysis and simulation studies using the ANN model provide better understanding of effects of input variables on output variables. The ANN model could be successfully used as the objective functions to find out the optimum solutions using GA for the above-mentioned study. It could find optimum percentage removal of chromium for varying height of the column.

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