Investigation of Constructed Wetlands Efficiency in Mercury Removal Using Genetically Generated Fuzzy Knowledge Bases

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ABSTRACT: Wetlands have been known as an efficient and low-cost technology in treating wastewater. Current design approaches lack essential parameters necessary to evaluate the removal of metals contained in waters discharged to constructed wetlands. Research shows a combination of experimental and computation modeling to assess the efficiency of mercury removal. Experimental investigations were conducted to investigate the ability of wetland floating and rooted plants to uptake mercury from water. Numerical modeling investigations were then carried out to: a) expand the results obtained in the experimental phase by examining the distribution of mercury forms in water; b) evaluating the amount of bioavailable mercury for plant uptake; c) verify the effects of pH, temperature, and chloride concentrations in water on Hg speciation. A fuzzy knowledge base was used to assess efficiency of wetlands for various conditions of mercury discharge. A genetic algorithm (GA) has been developed to automatically construct the knowledge bases used by fuzzy decision support systems (FDSS). The GA produces an optimal approximation of a set of sampled data from a certain amount of input information. The main interest of this method is that it can be used to automatically generate (without the help of an expert) a fuzzy knowledge base--i.e., the fuzzy sets on the premises and conclusions, and the fuzzy rules--. The GA uses two main contradictory optimization criteria, i.e., the approximation error and the complexity level of the knowledge base. The approximation error is computed as the root mean square error between the sampled outputs and the answers of the FDSS Fuzzy-Flou (an FDSS developed at École Polytechnique de Montreal, Canada, and the Technical University of Silesia in Gliwice, Poland) at the corresponding sampled input data. The complexity level is computed as the number of fuzzy rules contained in the knowledge base. The GA deals with many other criteria, e.g., the probability of crossover, the probability of fuzzy-sets displacement, the probability of fuzzy-rules reduction and the probability of mutation, that also control the optimization process. The findings of this research can be applied to wetlands (natural and constructed) were purification of: a) municipal; b) industrial; c) acidic; and d) agricultural wastewater is performed and applied in preparing environmental risk or impact assessments.
1. INTRODUCTION

Wetlands have been known as an efficient and low-cost technology in treating wastewater. It was reported that wetlands (natural and constructed) were used to purify: a) municipal; b) industrial; c) acidic; and d) agricultural wastewater. It should be mentioned that many environmental agencies do not encourage the use of natural wetlands in wastewater treatment; on the other hand, they try to preserve them to protect the wild life habitat. That will leave constructed wetlands (CW) to be the potential type of wetlands recommended for treatment of wastewater containing traces of metals (e.g. mercury).

Mercury has been used intensively by wide variety of industries because of its unique properties. Consequently, it was present at various levels in wastewater discharged. The ability of constructed wetlands to serve as a sink of mercury before entering larger aquatic systems has been investigated recently by El-Agroudy (1999). Study focused on the capability of constructed wetlands (Free Water Surface) to remove mercury from contaminated water/wastewater and reduce the widespread dispersion of the toxic substance to streams, rivers, reservoirs, and oceans. Mercury removal pathways considered in the study were uptake by plants.

Current design approaches of constructed wetlands lack essential parameters necessary to optimize their capabilities for mercury removal. There are many factors required to conduct a comprehensive design of a constructed wetland system to treat mercury-contaminated water, among them the influence of removal kinetics, hydraulic and thermal factors. An important factor, which affects the entire design procedure, is the residence time inside the treatment system. This factor depends on the type of the plants used in the system.

The most significant factors in choosing the types of plants are the efficiency of these plants in removing mercury from the water and their tolerance to its toxicity. Based on the literature reviewed, the use of specific plants for the purpose of treating wastewater in constructed wetlands, including Water Hyacinth (Eichhornia crassipes) and Reeds (Phragmites communis), was recommended. In addition to their efficiency in removing many pollutants from wastewater, Water Hyacinth and Reeds have the capability to accumulate different mercury compounds. The World Health Organization (1989) has published some data regarding mercury’s Bioconcentration Factor (BCF) by both plants. Water Hyacinth has the capability to accumulate mercuric chloride up to a BCF of 580; and Reeds accumulate mercury in the form of phenyl mercuric acetate to a BCF of 850.

Experimental investigations were conducted to investigate the ability of Water (floating plants) and Reeds (rooted plants) to remove inorganic mercury compounds from water. Kinetics of mercury removal by both plants in the concentration range of 5 to 150 ppb was investigated.

The experimental study (conducted in greenhouse) concluded that the uptake of mercury by plants is classified by a rapid phase followed by a much slower phase. It was shown that mercury was removed up to 98% by Reeds and 99% by Water Hyacinth during 72 hours. However, those investigations were not able to show if remaining mercury is bioavailable.

The results of the experimental investigation were then extended using numerical modeling to evaluate the bioavailable form of mercury for plant uptake and the impact of some environmental factors on mercury bioavailability. The analysis was carried out using MINTEQA2, a geochemical software developed by the USEPA. The software satisfies the specified conditions as well as computing equilibrium among the dissolved, adsorbed, solid, and gas phases in an environmental setting using an extensive database of reliable thermodynamic data.

Numerical modeling investigations were then carried out to examine the distribution of mercury forms in water and evaluating the amount of bioavailable mercury for plant uptake; b) verify the effects of pH, temperature, and chloride concentrations in water on Hg speciation; for five initial mercury concentrations (1E-7 to 1E-3 moles).

The investigation was based on changing one variable while the other factors were kept unchanged. The influence of each of these factors on mercury speciation was described. The mercury compounds considered in the final equilibrium solution, throughout all the investigations, are HgOH$^{+1}$, Hg (OH)$_3^{-1}$, Hg$^{+2}$, HgCl$^{+1}$, HgCl$_2$ (aq), HgCl$_3$ (aq), HgCl$_4$ (aq), and HgClOH (aq), where Hg$^{+2}$ was assumed to be only bioavailable form.

For design purposes a wider ranges of mercury concentrations in water and pH values have to be applied. The computer calculation had been, however, limited to some particular values. Therefore a new supplementary method was investigated.
2. METHODOLOGY

This paper describes the investigations carried out to specify the forms of mercury available for plants depending on some environmental parameters (e.g. wetland water quality, characteristics of wastewater discharged). The objective of these investigations was to develop a methodology for providing supplementary information (to the experimental results) for the optimum design of wetlands, and to enhance the extent of wetland involvement in the removal of mercury species.

Both experimental test and computation calculation using MINTEQA2 showed limitations (El-Agroudy, 1999). Computation methods were limited to a combination of three pH values, five initial total mercury concentrations, five initial chloride concentrations. It is obvious that in natural conditions the variability of those factors is extremely high. However, the design of CW has to include the high variability of physical, biological and chemical factors.

Therefore, the authors attempted to use fuzzy-logic knowledge. The GGFKB (Genetically Generated Fuzzy Knowledge Bases) prepared the data base which was able to obtain the bioavailable ionic mercury concentration for any value of the initial total mercury concentration in wastewater within the combination to any concentration of chloride in any pH condition.

In order to apply a genetic algorithm (GA) the data generated from experimental and computation phases were used to set fuzzy-rules and fuzzy-conclusions. The FDSS Fuzzy-Flou software permitted to obtain a series of solutions for bioavailable ionic mercury for plants in wetland. The solution can be applied for any particular situation where natural conditions satisfy the following combination of the parameters:
- initial concentration of total mercury is situated between E-7 to E-3 moles
- initial concentration of chloride is between E-8 and F-4
- pH value is between 5.26 and 8.

2.3.1 Fuzzy Decision Support Systems

In this section we present a rule-based approach to decision making using fuzzy logic techniques, based on the compositional rule of inference (CRI). This approach is used to handle uncertain (imprecise) knowledge and was developed in the sixties by L.A. Zadeh [1]. Such knowledge can be collected and delivered by a human expert (e.g. decision-maker, designer, process planner, machine operator, etc.). The CRI may be written in the form:

\[ U' = (C' \times A') \circ R \]  

where \( R \) represents the global relation that aggregates all the rules (knowledge base), \((A', B', ..., C')\) represents the inputs (observations) and \( U' \) represents the output (conclusion). The symbol \( \circ \) represents the CRI operator. Three defuzzification methods are usually available, i.e., center of gravity (COG), average of maximums (AOM) and the modified center of gravity (MCOG). In this paper, the COG is used for the defuzzification. The knowledge base consists of two components: the linguistic term base (database) and the fuzzy production rule base. The database is divided in two parts: fuzzy premises and fuzzy conclusions. Figure 1 shows a screen printout of the premises and conclusion (on the right), the fuzzy rules and settings (on the left) of the FDSS Fuzzy-Flou a software developed at Ecole Polytechnique (Canada) and University of Silesia (Poland)[2].

2.3.1 Genetic Algorithm

Genetic algorithms are stochastic optimization techniques based on the analogy of the mechanics of biological genetics and imitate the Darwinian-survival-of-the-fittest approach. A GA is generally characterized by:
- a coding scheme for each possible solution, using a finite string of bits (called a chromosome);
- a fitness value that provides the quality of each solution;
- an initial set of solutions to the problem, called the initial population, randomly generated or chosen on a priori knowledge;
a set of reproduction, mutation and natural selection operators, that allows the evolution of the population.

Each individual of a population is a potential FDSS Fuzzy-Flou knowledge base. They are encoded before applying four operations: reproduction, mutation, evaluation and natural selection, and finally decoded [3].

Reproduction

The evolution of the population is achieved by reproduction of the best individuals based on their ability to survive natural selection. This reproduction is performed by any of the three-following operators based on different initiating probability. [4]

- Simple crossover
Reproduction is mainly made by crossover of the genotype (chromosome) of two parents to produce the genotype of two children.

- Fuzzy-Sets Displacement
The displacement of the fuzzy sets is performed by randomly selecting a fuzzy set on a premise and moving it one step toward the left or right with an equal probability.

- Fuzzy-Rules-Reduction
The reduction of the number of fuzzy rules is performed by randomly selecting a fuzzy rule, and disabling it.

Mutation

Mutation is a random inversion of a bit in the genotype of a new member of the population. Mutation allows trying completely different solutions.

Evaluation

The capacity of each individual to survive natural selection is evaluated by two objective functions. The first objective function evaluates the capacity of a knowledge base to approximate the sampled data. This fitness value, denoted \( \phi_1 \), is computed as the root mean square error method. The second objective function evaluates the complexity of a knowledge base through its number of active fuzzy rules, which is denoted \( \phi_2 \).

The combination of these two contradictory objectives is made through a weighted sum, i.e.:

\[
\phi = \omega_1 \phi_1 + (1 - \omega_1) \phi_2, \quad (2)
\]

where the optimization criteria \( \omega_1 \); is the weight associated to \( \phi_1 \).

Natural selection

Natural selection is performed on a population by keeping the most promising individuals based on their fitness. This is equivalent of using solutions that are the closest to the optimum. For convenience, we keep the population size constant.

3. GENETICALLY GENERATED FUZZY KNOWLEDGE BASES

The learning process is applied on a set of data used to predict the bioavailable concentration of Hg\(_2\) based on three inputs the pH, the Initial Hg concentration and the initial Cl concentration. This means the fuzzy knowledge base will contain three inputs and one output.

The knowledge obtained by the genetic-based learning is shown in fig.2.

![Figure 2: Screen shot of the GGFKB](image)

Figure 3, shows a comparison between the measured values for the bioavailable ionic Hg\(_2\)--from the set of data--and the corresponding values obtained by the GGFKB.

The GGFKB was able to reproduce the tendency of the curve obtained from the set of data. However we still see some disparities especially for the low initial concentrations of Hg.

For the high initial concentrations of Hg, the reproduction is almost perfect, the remaining
The difference is due to the resolution chosen on the output of the genetic-based learning system.

![Figure 3: Bioavailable Hg\textsubscript{2} vs Initial Hg Concentration](image)

The set of data contains 45 entries, each entry was constructed to represent a unique fuzzy rule.

This type of sets makes it much easier to construct the knowledge base manually, since the fuzzy-rules are already designed. However, the GA tends to create a general model rather than a particular solution (a knowledge base that represents exclusively the set of data used to construct it), hence, the small differences that we see in fig.3.

Adding to this, the chosen coding system allows us the use of a maximum number of 8 fuzzy sets on the conclusion, each fuzzy set can be placed on 16 equally-distant positions, that makes it difficult to fit to the output values to the values of the set of data. However a simple and easy manual tuning is still possible, since the GGFKB are rather transparent knowledge base where it is very easy to perform a manual adjustment (on the position of the fuzzy sets and even the fuzzy rules).

4. POTENTIAL APPLICATION

Study demonstrated the successful use of Fuzzy Flou software to design of constructed wetlands. This method can be also used in the designing of other natural processes, which required an implication of numerous interrelated factors.

The potential applications of the above mentioned study are:

- To optimize the design of constructed wetlands to remove mercury or other metals from contaminated waters.
- To introduce an economical factor for treating wastewater.
- To establish an environmental criterion for protecting downstream contaminated wastewater.

The findings of this research could be also applied in preparing environmental risk impact assessments and could be considered as the first nuclei of establishing regulations (codes) governing the design of constructed wetlands to remove trace of metals from contaminated waters. However, a pilot field study is still necessary to validate the results.

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