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Optimization of depth of filler media in horizontal flow constructed wetlands for maximizing removal rate coefficients of targeted pollutant(s)

Saurabh Singh [a], Abhishek Soti [a], Niha Mohan Kulshreshtha [a], Nikhil Kumar [b], Urmila Brighu [a], Akhilendra Bhushan Gupta [a], Achintya N. Bezbaruah [c]

[a] Department of Civil Engineering, Malaviya National Institute of Technology, JLN Marg, Jaipur 302017, India
[b] Department of Electrical Engineering, Malaviya National Institute of Technology, JLN Marg, Jaipur 302017, India
[c] Nanoenvirology Research Group, Department of Civil and Environmental Engineering, North Dakota State University, Fargo, ND 58105, USA

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Highlights

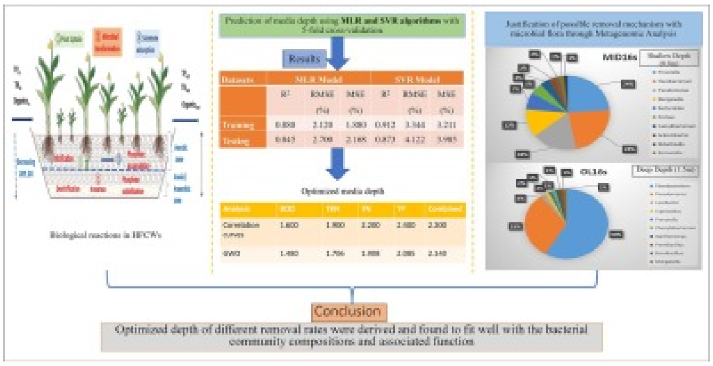
- Published data (n=1232) examined to derive a relation between d and removal rates K.
- Maximum volumetric K values (0.024 – 0.107 d^{-1}) were computed from performance data.

- SVR equation yielded d values closer to actual depths (R^2 0.873) than MLR equation.
- GWO (up to 1000 trials) based optimized d values derived using maximized K values.
- Optimized d values were $d_{BOD}=1.5$; $d_{TKN}=1.7$; $d_{TN}=1.9$, $d_{TP}=2.1$, $d_{all}=2.1$ m.

Abstract

Varying the depth of HFCW media causes differences in the redox status within the system, and hence the community structure and diversity of bacteria, affecting removal rates of different pollutants. The key functional microorganisms of CWs that remove contaminants belong to the phyla *Proteobacteria*, *Bacteroidetes*, *Actinobacteria*, and *Firmicutes*. Secondary data of 111 HFCWs (1232 datasets) were analyzed to deduce the relationship between volumetric removal rate coefficients (K_{BOD}, K_{TN}, K_{TKN}, and K_{TP}) and depth. Equations of depth were derived in terms of rate coefficients using machine learning approach (MLR and SVR) ($R^2=0.85$, 0.87 respectively). These equations were then used to find the optimum depth for pollutant(s) removal using Grey wolf optimization (GWO). The computed optimum depths were 1.48, 1.71, 1.91, 2.09, and 2.14 m for the removal of BOD, TKN, TN, TP, and combined nutrients, respectively, which were validated through primary data. This study would be helpful for optimal design of HFCWs.

Graphical abstract



Introduction

Natural treatment systems like constructed wetlands offer various advantages over traditional wastewater treatment technologies. These natural systems mimic the carbon, nitrogen, and phosphorous transformations occurring in nature with minimal operation and maintenance costs (Wang et al., 2022, Soti et al., 2022). The robust nature of natural systems is due to the presence of diverse microbial communities that have elaborate substrate spectrums (Zhao et al., 2021). These communities complement each other in different environmental conditions. Within the wetlands, different microbial communities remain active in different microenvironments due to the differences in substrate availability, dissolved oxygen, oxidation–reduction potential, temperature, etc. In fact, as we move deeper into the system, the oxygen availability is reduced (due to limited penetration of plant roots), and the fast-growing heterotrophic bacteria utilize carbon and deplete oxygen from the wastewater, thus reducing the C: N ratio (Kulshreshtha et al., 2022, Ajibade et al., 2021). This transformation allows autotrophic nitrifying bacteria to grow and carry out the first phase of nitrogen removal i.e. nitrification. As we move further deep, the conditions become anoxic and the denitrifying bacteria carry out the second phase of nitrogen transformation leading to the removal of nitrogen as dinitrogen gas (Tan et al., 2021). Further deeper regions may be anaerobic and may favor anaerobic ammonia oxidation (ANAMMOX) reaction for direct conversion of ammonia to nitrogen gas in the presence of nitrate ((Rampuria et al., 2020).

Ammonification, nitrification, and denitrification are the three primary processes by which microorganisms in CWs remove nitrogen from the environment (see supplementary material). Phylum *Proteobacteria* is the most abundant phylum in CWs and Proteobacterial sub-groups alpha-, beta-, and gamma-*proteobacteria* play a significant role in the treatment of a variety of wastewaters by removing nitrogen (Zhao et al., 2021, Ahmad et al., 2017a, Ajibade et al., 2021). The process of ammonification involves turning the organic nitrogen (Org-N) in wastewater into NH_4^+, which is then eliminated through various procedures (e.g., nitrification, volatilization, and plant uptake; (Xie et al., 2016, Ahmad et al., 2023). The most common genera of ammonifying bacteria are *Chitinophaga*, *Isoptericola*, *Bacillus*, and *Sinorhizobium* (see supplementary material). Ammonia-oxidizing bacteria (AOB) and archaea (AOA), which convert ammonium to nitrite; and nitrite-oxidizing bacteria (NOB), which convert nitrite to nitrate, are the two types of microorganisms involved in nitrification (Zhang et al., 2020). All of the currently recognized AOA belong to the phylum *Thaumarchaeota* (Wang et al., 2020). *Proteobacteria*, *Nitrospirae*, *Nitrospinae*, and *Thaumarchaeota* are some common phyla engaged in nitrification. The major nitrifying genera include *Nitrosomonas*, *Nitrobacter*, and *Nitrosospira. Proteobacteria*, *Bacteroidetes*, *Firmicutes*, and *Actinobacteria* are frequently found denitrifying bacteria in CWs. The major denitrifying genera are *Tauera*, *Thiobacillus*, *Thermomonas*, and *Arenimonas. Dechloromonas*, *Ferrobacterium, Hydrogenophaga, Zoogloea*, and *Aeromonas* were the most common types of heterotrophic nitrification and aerobic denitrification (HNAD) bacteria. *Thiobacillus* and *Sulfurimonas* are the most common sulphur autotrophic denitrifying bacteria, both of which are members of the phylum *Proteobacteria*. Reports have demonstrated that denitrifying genera like *Vibrio, Clostridium*, and *Desulfovibrio* are able to carry out the dissimilatory nitrate reduction to ammonium (DNRA) process (Zhang et al., 2020, Ahmad et al., 2017b).

Phosphorus-accumulating organisms (PAOs) are the principal biological phosphorus removal agents in CWs because of their ability to take up phosphate from wastewater and store it in their cells while undergoing both aerobic and anaerobic respiration (Tan et al., 2021). The *Proteobacteria* including *Alphaproteobacteria*, *Betaproteobacteria*, and *Gammaproteobacteria* are primarily responsible for the majority of phosphorus removal (Huang et al., 2019, Lv et al., 2021). *Alphaproteobacteria* families *Rhodobacteraceae* and *Rhizobiaceae* may absorb volatile fatty acids under aerobic conditions and convert them into polyhydroxyalkanoates (Lv et al., 2021, Ahmad et al., 2019). In addition to PAOs, denitrifying phosphorus-accumulating organisms (DNPAO) and phosphorus-solubilizing bacteria (PSB) have been identified in CWs. PSB such as those of the *Corynebacterium* and *Enterobacter* genera use organic acids (such as oxalic and citric acids) to convert insoluble phosphorus in the soil into a form that can be taken up by plants (Wang et al., 2020). Under anoxic conditions, DNPAO can take up polyphosphate using NO_3/NO_2 as electron acceptors (Wang et al., 2020). Organophosphate hydrolases that hydrolyze organophosphate esters are produced by species like *Brevundimonas* and *Chlorobaculum*, while the genus *Variovorax* can use insoluble phosphate as a phosphorus source for growth. (Wu et al., 2020). As these microorganisms have their own specific niches, we can say that the type of microbial transformations favored and the end products generated are likely to be determined by the depth of the wetland. It follows that the depth of the system may be altered for facilitating the preferred transformations (Zhao et al., 2021).

The depth of the wetland is an important consideration from the economic prospect as well. Increasing the depth of the system to increase the treatment capacity within the available land area without affecting (or enhancing) the system performance would be highly desirable in regions with limited land availability (Shimako et al., 2018). Increasing the depth of the HFCW has been reported to favor better nitrogen removal (Rampuria et al., 2020). However, going too deep may be challenging from an engineering point of view and may incur an additional pumping cost. Thus, it is important to determine the trade-off depth to achieve the desired goal. The outcome required may be dependent upon the prevailing environmental standards and may also vary as per the intended application/discharge of the treated wastewater (Zhang et al., 2021).

This paper deals with determining the optimal depth of the horizontal flow constructed wetlands for the desired removal – only organics/ organics and nutrients/ only nutrients etc. Due to the complex nature of the problem and different possible scenarios, a machine-learning (ML) approach was followed for the simultaneous optimization of more than one rate coefficient. Grey wolf optimization (GWO) which mimics the natural social hierarchy systems was used for this optimization (Chen et al., 2021). The GWO is applied when the dependent parameter depends on multiple parameters or the datasets show non-linear behaviour (Zhu et al., 2022). This optimization technique was applied to datasets to find the optimum depth of HFCWs for pollutant(s) removal.

The present study employs a novel approach to determine the optimum depth of horizontal flow constructed wetlands by maximizing the removal rate coefficients for different pollutants, individually and in combination, using machine learning tools. The primary goal was to determine the optimum depth of HFCWs by simultaneously maximizing the removal rates of the various pollutants (and their combinations) to minimize the area requirements of field HFCWs, which are generally highly overdesigned. Also, the deep HFCW systems are useful for nutrient removal as evidenced by the metagenomic results showing an abundance of heterotrophic nitrifiers and aerobic denitrifiers as well as phosphate-accumulating bacteria in deeper stretches. Attaching the metagenomics with the creation of niches of specific microorganisms can help customize pollutant removal (combination of organics, N, and P based on the intended standards to be met).

The review of the major functional microorganisms has helped us understand and investigate the mechanisms of pollutant removal by microorganisms in CWs, as well as the effects of pollutants in wastewater on the microorganisms. The primary goal was to determine the optimum depth of HFCWs by simultaneously maximizing the removal rates of the various pollutants (and their combinations). The study would aid in optimizing the area required for HFCWs depending upon the required treatment levels for target pollutants. Based on the field condition, suitable design assumptions can be derived from this work, which can substantially reduce the surface area requirements. It can help evolve CWs as a competitive technology in the domestic wastewater treatment industry, especially in urban settings.

This study aimed to find the equations for calculating the media depth using MLR and SVR algorithms and correlation curves. These equations were further used for optimization using the GWO. The main objective was to find the optimum depth of HFCWs for the removal of various pollutants (and their combinations) by simultaneously maximizing their removal rates.

Section snippets

Data collection

The secondary datasets of 111 HFCWs (1232 datasets) were extracted from research papers from sources like PubMed, ResearchGate, Web of Science, and Scopus. These research papers were published between 2004 and 2022. These papers are searched on websites with the keywords - ‘Horizontal flow constructed wetlands (HFCWs)’, ‘design of HFCWs’, ‘Performance efficiency of HFCWs’, and ‘depth optimization of HFCWs’. The final dataset consisting of 111 HFCWs contained only the HFCWs treating domestic …

Data Pre-processing

The DW analysis was performed to check autocorrelation between the influent’s parameter with the depth of media by statistical regression analysis. DW values of Surface area, temperature, OLR, detention time, K_{BOD}, $K_{TKN,}$ $K_{TN,}$ and K_{TP} lie in the acceptable range of 1.5 to 2.5, and it can be inferred that autocorrelation exists between the variables with respect to the depth of media. The distribution of datasets (distance from the mean) was checked by gaussian distribution curves. This was done …

Conclusion

An overview of the functional microorganisms involved in the removal of nitrogen and phosphorus in HFCWs and its validation through a detailed metagenomic analysis of field wetlands showed that the phylum *Proteobacteria* was the most dominant among others like *Bacteroidetes, Actinobacteria*, and *Firmicutes*. The deep HFCW systems are useful for nutrient removal as evidenced by the abundance of heterotrophic nitrifiers and aerobic denitrifiers as well as phosphate-accumulating bacteria. Expressions …

CRediT authorship contribution statement

Saurabh Singh: Conceptualization, Methodology, Investigation, Writing – original draft. **Abhishek Soti:** Writing – review & editing. **Niha Mohan Kulshreshtha:** Conceptualization, Methodology, Investigation, Writing – review & editing. **Nikhil Kumar:** Conceptualization. **Urmila Brighu:** Writing – review & editing. **Akhilendra Bhushan Gupta:** Conceptualization, Supervision, Funding acquisition, Writing – review & editing. **Achintya N. Bezbaruah:** Writing – review & editing. …

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. …

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