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Controlling Biochemical Oxygen Demand in the Multi-Soil-Layering using Neural Network tool

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Abstract

The effect of a set of environmental parameters on the pollution indicators BOD_5, in Multi-Soil-Layering (MSL) has been studied using neural networks (NNs) and multiple regression analysis (MRA). The obtained results show that, NNs may be used as a practical tool to control the wastewater treatment. The process of rural wastewater treatment by MSL, which is an innovative system used for the first time in Morocco, was studied by modelling the relationships between a set of environmental factors and BOD_5 based upon 163 sampling. The models of interaction between variables were tested by using both MRA and NNs methods. Considering the relevant factors obtained from the MRA, a correlation coefficient (R^2) of 0.58 with a standard deviation (S) of 0.76, approve that, there is no significant linear connection between different environmental factors and BOD_5. The non-linearity of the relationship has led us to use a NNS methods. The architecture of the best model obtained by NNs is MLP 5-1-1 with a R^2 of 0.82 and a Root Mean Square (RMS) of 0.80. The best models established were found to be nonlinear. Obtained results suggest that NNs may be used as a practical tool to control the wastewater treatment in the MSL.

1. Introduction

The hydraulic potential in Morocco is limited, droughts are more frequent, resulting of climate change, and increasing water demand relating to the population growth and socio-economic development.
Wastewater is one of the most important sources of urban, rural and industrial pollution, due to the chemical and biological pollutants that it contains. Wastewater infrastructure in rural areas are either poorly developed or non-existent. Most of rural communities are suffering from pollution, and the potential for illness caused by untreated sewage discharged directly in the environment. In the absence of collection and treatment systems, sewage disposal is often left to the discretion of homeowners. In many cases, untreated sewage is discharged into surface waters or the landscape, contaminating already dwindling surface water and groundwater resources. This practice will continue unabated unless appropriate and affordable treatment systems are made available.[1]
Innovative and low cost technologies such as MSL system can contribute to rural wastewater treatment in small communities where technical and financial resources are usually limited.
MSL systems are characterized by several advantages such as low capital costs, small area demand, no energy consumption and maintenance requirements, no frequent clogging, the application of high hydraulic loading rate (HLR) and an effective life that was estimated to be longer than 20 years for domestic wastewater treatment [2]. The MSL system has been successfully used in Japan, China, USA and Thailand to treat different types of wastewater [2] .

MSL systems were based on the functioning of natural systems and the treatment processes involve complex interactions between soil, water and microorganisms. Various processes regulate pollutant removal in MSL systems including filtration, adsorption and biodegradation[2] .

The MSL systems are composed of low cost materials locally available in rural communities. Two layers compose the MSL system: aerobic and anaerobic layer that are arranged in a brick-like pattern. The aerobic permeable layer consists of gravel, zeolite or Perlite. The anaerobic layer composed of a mixture of soil, iron particles, sawdust and charcoal [3]. MSL technology were proved efficient in removal of suspended solids, organic matter, nitrogen and phosphorus but the removal of fecal bacterial indicators and pathogens is relatively moderate due to the high porosity level and coarse pore spaces of the water permeable gravel layers in the MSL system.[4]

In this paper, we identify and quantify the effect of the main environmental parameters affecting the removal rate of BOD_5. This was achieved by modelling using both MRA and NN models. Furthermore, we attempt to show how NN techniques are useful to explicit nonlinear relationships between environmental parameters and BOD_5 during the purification of wastewater by MSL. The best-established model may be used as tool in the control of the treatment quality by MSL.

2. Experimental details

2.1. *Data sources*

In order to find the relationships between environmental parameters and BOD_5 during the purification of wastewater by MSL, five laboratory-scale MSL systems were built and monitored. The first small scale pilot, which was 30 cm deep, 36 cm wide, 65 cm high and a HLR of 200 $l/m^2/day$. The four others were installed at the village Talat Marghen under the Aghouatim rural community in Marrakech governorate in Morocco. They are cylindrical plastics with a height of 65 cm and a diameter of 41 cm. with different HLRs: 250, 500, and 1000 $l/m^2/day$. MSL pilot plants were alimented continuously by domestic wastewater.

This first experiment was conducted from 17 February 2013 to 19 May 2014 with 63 samples. While the four others were monitoring between the periods of 24 July 2014 to 18 June 2015, with 25 samples for each pilot.

Figure 1 show the structure of MSL processes used in this study.[1]

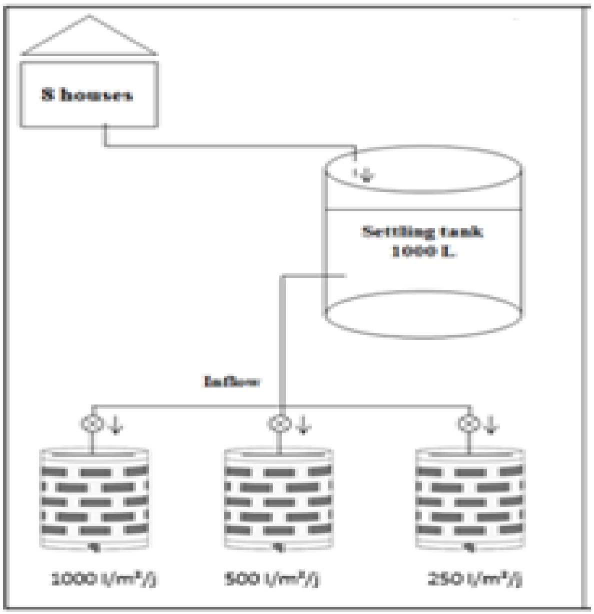

Figure 1: Schematic diagram of MSL processes used in the village Talat Marghen.

Inflow and effluent wastewater were collected at the same time once per 2 week using plastic bottles for chemical assays, and in sterile glass bottles for bacteriological studies .

Samples were analyzed for various physical and chemical parameters in accordance with the Standard Methods [5, 6]. Parameters were experimented in influent and effluent wastewater was tested 3 times.

Analysis of physic-chemical variables was performed on raw sample and treated wastewater using MSL systems include the following parameters:
pH, Temperature (T), Electrical Conductivity (EC), Dissolved Oxygen (DO), Total Suspended Solids (SS), Biochemical Oxygen Demand (BOD_5), Chemical Oxygen Demand (COD), Ammonium (NH_4^+), Total Kjeldahl Nitrogen (TKN), Total Nitrogen (TN) and Total Phosphorus (TP).

2.2 *Modelling*

The exploratory analysis of experimental data frequently used statistical tools. In this study, we analyzed the physical and chemical data by a linear modeling with MRA. The non-mathematical significance of the results led us to model the output BOD_5 depending on other input variables by NNs method. This article presents detailed applicability of artificial neural networks (ANNs) and their contribution to the study of the evaluation of the carbon pollution output using the MSL.

2.2.1 Linear analysis of the physical and chemical data by multiple linear regression (MLR)

The established relationships between environmental parameters and BOD_5 were carried out using the Principal component analysis (PCA) and MRA. Both methods aim at providing the equations describing the relationship between the parameters influencing the treated wastewater.

2.2.2 Nonlinear analysis of the physical and chemical data by ANNs

By training a nonlinear system of multiple variables, ANN can predict the independent variable [7]. Consequently, ANNs approximate technical systems complexes, which are difficult to model by conventional statistical methods.
The established relationships between environmental parameters and BOD_5 were carried out using the NNs technique. The analysis of physical-chemical data used to create the model of the ANN providing BOD_5 removal by the MSL system were analyzed using the STATISTICA neural network software version 4.0.
As there is a large number of structures of ANN, it is necessary to choose an appropriate NNs development of this study. We started our train NNs system by varying parameters that significantly influence the results of predicting such as architecture of ANN, the activation function, number of hidden unit, the number of iterations. To determine the best network parameters (number of hidden neurons, activation function, number of iterations, etc.) which gives a satisfactory prediction, we made a series of tests for the number of hidden neurons between 1 and 5, with different activation function possible, architecture and algorithm, which are governed by the iterations of from 20 to 60. The optimize NN model used in this work has three layers: an input layer having five neurons consisted by the environmental parameters, a hidden layer and one unit in the output layer representing BOD_5 concentration .
Finally, we analyzed the RMS and the R^2 to choose the best model taking into account issues of performance and generalization.
Mathematically, as illustrated in Figure 2, each neuron receives input vector form then calculates a weighted sum of its inputs so that the result is then passed through the activation function to create an exit.

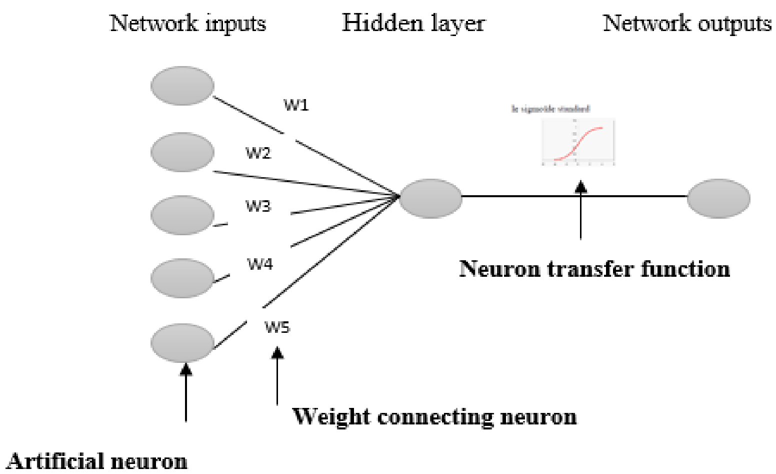

Figure 2: Typical architecture of the NN

3. Results and Discussion

3.1 Effect of environmental factors on BOD_5 removal using linear model

After calculating the correlation coefficients between the input parameters to reduce the number of input values and refine linear regression, using the PCA, we moved on to the second part of the series of statistical analysis of the data using the method of MRA. The uncorrelated parameters used in the MRA are pH, COD, TN, $NH_4^+$and a HLR.
Two criteria are used to evaluate the performance of models: R^2 and the S.
The best MRA model, found is given below (Equation 1):
Equation 1:

$$\mathbf{BOD_5\ (mg/l) = 6.91\ pH + 0.63\ NH_4^+ + 0.04\ HLR - 46.38}$$

pH: Hydrogen potential
NH_4^+: Ammonium
HLR: Hydraulic Loading Rate

The statistical parameters of the model are: n = 163, $R^2 = 0.58$, S = 0.76

3.2 Effect of environmental factors on BOD_5 removal using nonlinear analysis
We considered all uncorrelated parameters cited above, and using ANNs, the architecture of the best model obtained as follows:

- MLP 5-1-1.
- Activation function: Sinus.
- Architecture: Multilayer Perceptron (MLP).
- Algorithm: Broyden-Fletcher-Goldfarb-Shanno (BFGS).

The statistical parameters used to evaluate the performance of the model are: RMS and R^2.

After optimization (50 cycles) of the weights of connections (Table 1), we obtained a model for which the predicted and observed values of BOD_5 are highly correlated (R^2= 0.82). The configuration of the NN was 5 – 1 – 1.
Table 1: Weight of connections between neurons.

Variable*	***pH***	***COD***	***TN***	***HLR***	***NH_4^+***	**B**
Hidden neurons	0.288	0.063	-0.079	1.048	0.451	0.448

*Hydrogen potential (pH), Chemical Oxygen Demand (COD), Total Nitrogen (TN) Ammonium (NH_4^+), Hydraulic Loading Rate (HLR) and Bias (B)

The statistical parameters of the model are: n = 163, $R^2 = 0.82$, RMS = 0.80
Measured and predicted values of BOD_5 by MRA and NNs are illustrate in figure 3.

We attempt the evaluation of the contribution of each environmental parameter to the whole model. We also calculated the contribution of variables of equation according to the Gore method [8]. Results are reported in table 2.
Table 2: Contribution of variables to BOD_5 for the MRA and NN models.

VARIABLE*	***HLR***	***pH***	***NH_4^+***	***TN***	***COD***
MRA MODEL CONTRIBUTION (%)	65	13	22	-	-
NN MODEL CONTRIBUTION (%)	53	17	26	1	3

**Hydraulic Loading Rate (HLR), Hydrogen potential (pH), Ammonium (NH_4^+), Total Nitrogen (TN) and Chemical Oxygen Demand (COD)*

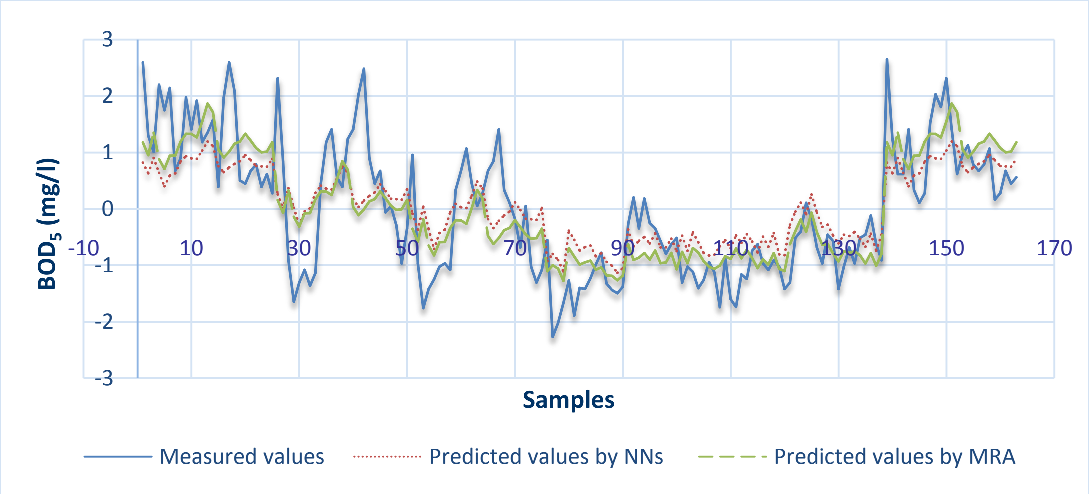

Figure 3: Measured and predicted values of BOD_5 by MRA and NNs

It is the first time; we can quantify the effect of each environmental parameter on BOD_5 removal. Comparing the two models found by MRA and NNs, we note, first, that the three parameters HLR, pH and NH_4^+ appears in both models, with different proportions, 65%, 13%, and 22% in the linear model, while are 53%, 17% and 26% in the non- linear model, which we add 3% and 1% of COD and TN that appear only in NN model. Moreover, the correlation coefficient obtained by MRA of 0.58 is too low, whereas that obtained by NN is 0.82, this indicates that the result is satisfactory, and that the model which explain better the behavior of the MSL is not linear.

According to the results, we can conclude that the second is statistically valid with a RMS less than 0.80 and a R^2 of 0.82 confirming that our model is very strong.

The contribution of HLR, NH_4^+, pH, COD and TN were 53, 26, 17, 3 and 1 % respectively and clearly explained by the model: Firstly, Wakatsuki et *al.* [9] explained when the wastewater is discharged into the MSL systems, organic matter is adsorbed on the soil specific surface area and subsequently decomposed by microorganisms. According to Deronzie et *al.* [10], the bacteria ensuring the treatment of the organic pollutant load need for their metabolism many chemical elements. Nitrogen is the most important component of the bacterial cell, accounting for about 5% of its dry matter. Thing approved by our model where nitrogen influences the removal rate of BOD_5 from its MSL by about 26%.

According to our model, the pH affect the elimination rate of carbon pollution with medium contribution of 17%. Indeed. According to the literature, it has been approved that the most favorable pH values for biological processes are between 6.5 and 7.5 [11].

As for the HLR, and as approved by [1, 12], an increase in HLR reduced the hydraulic retention time in the MSL system, resulting in a decrease in the percentage of pollution elimination. Based on our model, HLR influences the BOD_5 removal rate by approximately 53%.

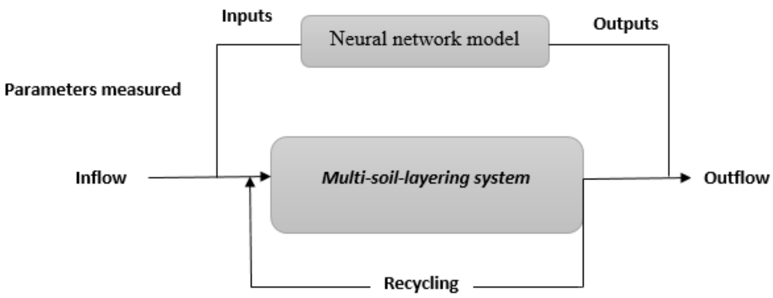

Figure 4: Pollution control in biological wastewater treatment.

According to the results obtained, one concludes that NNs models are the adapted tool to account for the relationships between environmental parameters and BOD_5. The obtained model suggests their use as control of MSL systems on the basis of the parameters studied. The calculated BOD_5 may be compared as the standardized threshold value. Thus, if BOD_5 (calculated) < BOD_5 according to the limits (norms), one achieved a good treatment; if not the non-sufficiently treated batch will be recycled. General scheme of the organogram is given in figure 4.

Conclusions

According to the obtained results, we conclude that nonlinear models are the adapted tool to account for the relationships between environmental factors and the MSL process of wastewater treatment. The main environmental parameters affecting the removal rate of BOD_5, achieving by modelling using NN models are HLR, NH_4^+, pH, COD and TN of the inflow wastewater, with a contribution of 53, 26, 17, 3 and 1 % respectively. This established model allows us to be used as tool in the control of the treatment quality by MSL.

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