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Modelling of Phosphorus Removal in Integrated Constructed Wetlands Using Adaptive Neuro-Fuzzy Inference System

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ABSTRACT

Adaptive neuro-fuzzy inference system (ANFIS) models were developed to elucidate the removal of molybdate reactive phosphate (MRP) and to predict effluent concentrations in integrated constructed wetlands (ICW). The ANFIS models were developed and validated with a four-year data set from a full-scale ICW treating domestic wastewater. The models highlighted the importance of physicochemical parameters in the removal of MRP in ICW systems. High water temperature, dissolved oxygen, and electrical conductivity; and low oxidation-reduction potential were associated with high rate MRP removal. Findings indicate that ANFIS could predict the effluent MRP variation quite strongly. The simulated effluent MRP concentrations well fit measured concentrations. Effluent MRP were predicted to a reasonable accuracy (MASE = 0.12) by using input variables which can be easily monitored in real time as sole predictor variables. The validated model could be a useful tool for the rapid estimation of MRP removal in ICW systems. The rapid prediction with ANFIS provides an inexpensive alternative to laborious laboratory analyses and also serves as a management tool for day-to-day process control of ICW systems.

Keywords: Adaptive neuro-fuzzy inference system; constructed wetland; domestic wastewater; phosphorus; prediction

1. INTRODUCTION

Contaminants removal in integrated constructed wetlands (ICW) (Scholz et al., 2007) occurs through complex biological, chemical and physical processes that are associated with system components such as wetland plants, substrates and microorganisms. The removal of phosphorus (P) occurs mostly in the form of orthophosphates, and the main mechanisms include soil accretion, media adsorption, precipitation, plant and microbial uptake, leaching, mineralization, and burial (Vymazal, 2007).

However, the accumulated P can be remobilized to the water environment as the adsorption processes are saturated and physicochemical conditions in the wetland change (Dong et al., 2012). The physicochemical parameters (e.g. temperature, pH, oxidation-reduction potential, etc.) are particularly important for the removal of pollutants in ICWs as many abiotic processes, including adsorption, photodegradation and chemical degradation depend on these

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parameters (Hijosa-Valsero et al., 2011).

Several mathematical and statistical modelling approaches can be used to simplify the contaminant treatment processes and are widely applied to describe the relationships between treatment efficiency and impact factors (Dong et al., 2012; Hijosa-Valsero et al., 2011; Kumar and Zhao, 2011; Rousseau et al. 2004). However, as the removal processes and impact factors have been shown to exhibit nonlinear interactions (Kadlec and Knight, 1996; Rousseau et al., 2004) and datasets have various distributions besides normal and exponential, novel nonlinear models, which have the ability to provide a comprehensive description of contaminant removal processes and the effects of additional physicochemical and environmental variables require further research. Artificial intelligence (AI) models such as various Artificial Neural Networks (ANN) and Fuzzy Logic (FL) models show huge promise in this regard and are recommended for further scientific studies (Kumar and Zhao, 2011).

The aim of this paper, therefore, was to investigate the existence of clear relationships between physicochemical parameters (temperature, pH, electrical conductivity, dissolved oxygen and oxidation-reduction potential) in ICW systems and molybdate reactive phosphate (MRP) removal, by using adaptive neuro-fuzzy inference system (ANFIS) models. The specific objectives were to (1) elucidate the impact of physicochemical water quality parameters on MRP removal, and (2) to assess ANFIS models for the rapid prediction of MRP concentrations in integrated constructed wetland effluents.

2. MATERIALS AND METHODS

2.1. Study site description

The integrated constructed wetland (ICW) treatment system at the centre of the study is located at Glaslough in County Monaghan, Ireland (06°53’37.94” W, 54°19’6.01” N). The ICW (Fig. 1) comprises a small pumping station, two sedimentation ponds, and a sequence of five shallow and vegetated wetland cells. Hydraulic characteristics of the wetland cells are presented in Table 1. The ICW system was commissioned in October 2007, to treat sewage from Glaslough village.

The design capacity of the ICW system is 1,750 p.e. The functional water area of the ICW cells is 3.25 ha within a curtilage area of 6.74 ha. The wetland cells have no artificial lining. Excavated local soil material was used to construct the base of the wetland cells and was compacted to a thickness of 500 mm to form a low permeability liner. Furthermore, the local soil, which comprised a mixture of coarse and fine-grained materials, namely alluvium, organic soils, tills, and gravel, was used as the main wetland substrate material.

Influent primary domestic wastewater from the village is pumped directly into a receiving sedimentation pond at approximately 123 ± 2.02 m^3/d. The system contains two sedimentation ponds that can be used alternately. From the sedimentation pond, the wastewater subsequently flows by gravity sequentially through the five earthen-lined cells. The effluent of the last cell discharges directly into the adjacent Mountain Water River (Fig. 1).

The wetland cells were planted in a club pattern, and the main ones were *Carexriparia* Curtis, *Phragmitesaustralis* (Cav.) Trin. ex Steud., *Typhalatifolia* L., *Iris pseudacorus* L., and *Glyceria maxima* (Hartm.) Holmb. This currently includes a complex mixture of *Glyceriafluitans* (L.) R. Br., *Juncuseffusus* L., *Sparganiumerectum* L. emend Rchb, *Elismanatans* (L.) Raf., and *Scirpuspendulus* Muhl.

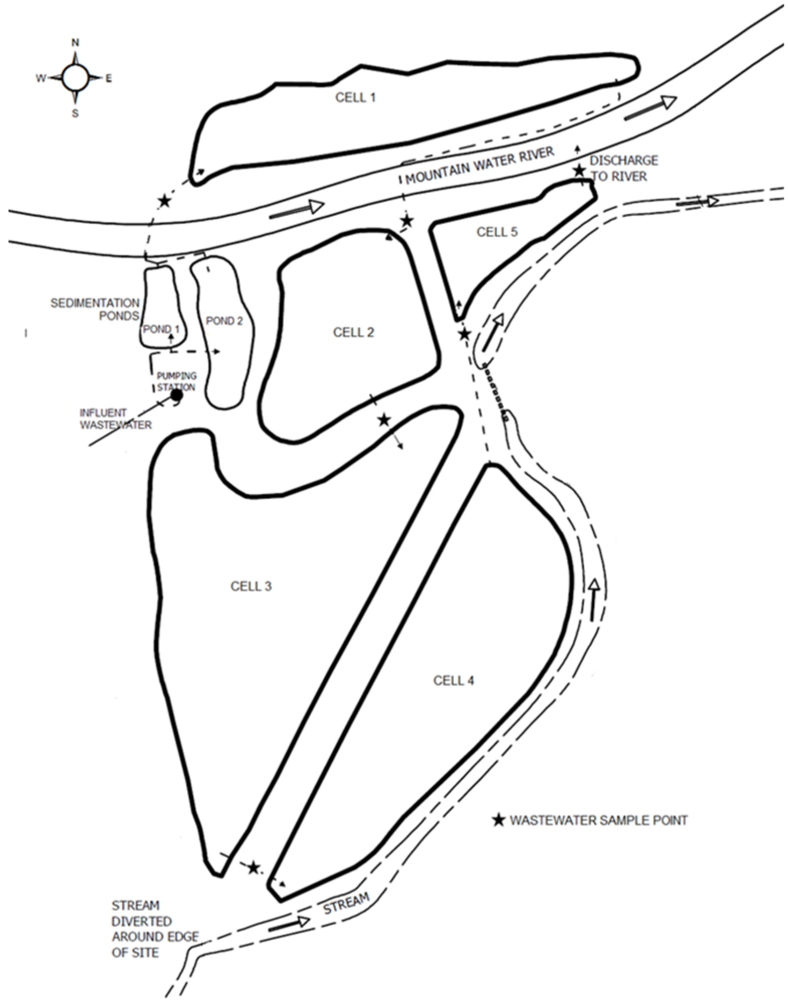

Figure 1 Schematic diagram of integrated constructed wetland at Glaslough in Ireland

Table 1 Dimensions of the integrated constructed wetland (ICW) cells at Glaslough in County Monaghan, Ireland

ICW section	Area (m^2)	Depth (m)	Total volume (m^3)	Effective volume (m^3)
Sedimentation pond 1	285	0.45	128.3	85.5
Sedimentation pond 2	365	0.45	164.3	109.5
Cell 1	4664	0.42	1958.9	1399.2
Cell 2	4500	0.38	1710.0	1350
Cell 3	12660	0.32	4051.2	3798
Cell 4	9170	0.36	3301.2	2751
Cell 5	1460	0.29	423.4	423.4
Total wetland	33104	-	11737.3	9916.6

2.2 Adaptive neuro-fuzzy inference system

The adaptive neuro-fuzzy inference system (ANFIS) is a Takagi-Sugeno-type (Jang, 1993; Sugeno and Kang, 1988; Takagi and Sugeno, 1985) fuzzy inference system (FIS) implemented within the framework of adaptive neural networks. Based on a multilayer feed-forward network, ANFIS uses neural network learning algorithms and fuzzy reasoning to map a set of inputs to the output. The network structure consists of nodes and directional links through which the nodes are connected. In this network, part or all of the nodes are adaptive, which means that the output of each node depends on the parameter(s) pertaining to it. The parameter(s) should be changed to minimize a prescribed error measure according to the network's learning algorithm. Each node performs a particular function (node function) on incoming signals as well as providing a set of parameters pertaining to this node. The nature of node functions may vary from one node to the other, and the choice of each node function depends on the overall input-output function that the adaptive network is required to carry out (Jang, 1993). To reflect different adaptive capabilities, an ANFIS uses both circle and square nodes, whereby a square (adaptive) node has parameters while a circle (fixed) node has none. The architecture of a typical ANFIS with two inputs, two fuzzy *if-then* rules and one output for the first-order Takagi and Sugeno's type fuzzy model (Takagi and Sugeno, 1985), where each input is assumed to have two associated membership functions (MFs) is shown in Fig. 2.

For a first-order Takagi-Sugeno fuzzy model (Takagi and Sugeno, 1985), a typical rule set with two fuzzy*if-then* rules can be expressed as (Jang, 1993; Wang and Elhag, 2008):

Rule 1: If x is A_1 and y is B_1 then $f_1 = p_1 x + q_1 y + r_1$

Rule 2: If x is A_2 and y is B_2 then $f_2 = p_2 x + q_2 y + r_2$

where: A_1, A_2 and B_1, B_2 are the MFs for the inputs x and y, respectively; P_{ij}, Q_{ij} and $r_{ij} = (i, j = 1, 2)$ are consequent parameters.

The architecture of a typical ANFIS consists of five layers (Fig. 2), and every node in a given layer performs particular functions in the ANFIS such as *input*, *fuzzification*, *rule inference*, *normalization*, and *defuzzification*. A detailed description is provided in Jang (1993) and Jang et al. (1997).

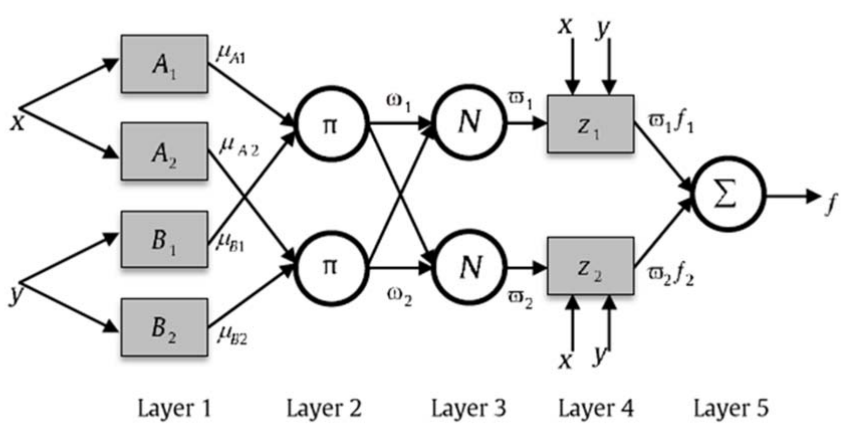

Figure 2 ANFIS structure for a two-input first-order Sugeno model with two rules

2.2.1 ANFIS architecture layer 1

All the nodes in this layer are adaptive nodes. Each node generates membership grades of a linguistic label (Chedid et al., 2000). Parameters in this layer are referred to as premise parameters, S_1, and they can be trained using the ANFIS learning algorithm (Jang, 1993). The outputs of this layer are given by:

$$\begin{aligned} o_{Ai}^1 &= \mu_{Ai}(x) \; i = 1,2 \\ o_{Bj}^1 &= \mu_{Bj}(y) \; j = 1,2 \end{aligned} \quad \text{(eq. 1)}$$

where x and y are crisp inputs to node i, j, and A_i and B_j are linguistic labels such as low, medium, high, etc. from fuzzy set $A = (A_1, A_2, B_1, B_2)$ associated with the node, characterized by appropriate MFs. The MFs determine the degree to which x and y satisfy the quantifiers A_i and B_j, and could be triangular, trapezoidal, Gaussian, Bell-shaped or other shape functions.

2.2.2 ANFIS architecture layer 2

Every node in layer 2 is a fixed node and calculates the firing strength of each rule via multiplication of the incoming signals (Jang, 1993). The firing strength means the degree to which the antecedent part of the rule is satisfied. The outputs of this layer are represented as:

$$o_{ij}^2 = \omega_{ij} = \mu_{Ai}(x) \times \mu_{Bj}(y), \quad i, j = 1,2 \quad \text{(eq. 2)}$$

2.2.3 ANFIS architecture layer 3

Nodes in layer 3 are also fixed nodes and compute the normalized firing strength of each rule. The i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of firing strengths of all rules (Jang, 1993), described as:

$$o_i^3 = \varpi_i = \omega_1 \cdot \left(\sum_{i=1}^{n} \omega_1 \right)^{-1}, \quad i = 1,2 \quad \text{(eq. 3)}$$

2.2.4 ANFIS architecture layer 4

Each node in this layer is an adaptive node, whose output is simply the product of the normalized firing strength and a first-order polynomial, expressed as (Jang, 1993):

$$o_{ij}^4 = \varpi_{ij} f_{ij} = \varpi_{ij} \left(p_{ij} x + q_{ij} y + r_{ij} \right), \quad i, j = 1,2 \quad \text{(eq. 4)}$$

Where ϖ_{ij} is the output of layer 3 and p, q, r are referred to as the consequent parameter set S_2, which can also be trained using ANFIS learning algorithms.

2.2.5 ANFIS architecture layer 5

The single node in this layer is a fixed node labeled Σ, which computes the overall output as the summation of all incoming signals (Jang, 1993):

$$o_1^5 = \sum_{i=1}^{2} \sum_{j=1}^{2} \varpi_{ij} f_{ij} = \sum_{i=1}^{2} \sum_{j=1}^{2} \varpi_{ij} \left(p_{ij} x + q_{ij} y + r_{ij} \right) \quad \text{(eq. 5)}$$

When the values of the premise parameters (membership parameters) are fixed, the overall output can be expressed as a linear combination of the consequent parameters (p_{ij}, q_{ij}, r_{ij}). Thus, the output, f can be rewritten as:

$$f_{ij} = \sum \sum \left[\left(\varpi_{ij} x \right) p_{ij} + \left(\varpi_{ij} y \right) q_{ij} + \left(\varpi_{ij} \right) r_{ij} \right] \quad \text{(eq. 6)}$$

Overall, the ANFIS architecture has two adaptive layers: Layer 1 and Layer 4. Layer 1 has modifiable parameters a_{ij}, b_{ij}, c_{ij} and relates to the input MFs. Layer 4 has modifiable parameters p_{ij}, q_{ij}, r_{ij} pertaining to the first-order polynomial. The task of the learning algorithm for this ANFIS architecture is to tune all the modifiable parameters to make the ANFIS output match the training data. Learning or adjusting these modifiable parameters is a two-step process, which is known as the hybrid-learning algorithm. In the forward pass of the hybrid learning algorithm, the premise parameters are held fixed, node outputs go forward until Layer 4 and the consequent parameters are identified by the least squares method. In the backward pass, the consequent parameters are held fixed, the error signals propagate backwards and the premise parameters are updated by the gradient descent method. The detailed algorithm and mathematical background of the hybrid-learning algorithm can be found in Jang (1993).

2.3 Model development

2.3.1 Data variables selection

The general idea for the model development was to predict effluent concentrations of molybdate reactive phosphate (MRP), using other parameters, which are cost-effective, quicker and easier to measure. Based on this consideration, five variables, which can be measured relatively quickly, namely, water temperature (T), pH, dissolved oxygen (DO), oxidation-reduction potential (ORP) and electrical conductivity (EC), were selected. Weekly data records for MRP with no missing values, collected over the period of February 2008 to March 2012 from the integrated constructed wetland at the centre of this study, were selected for modelling. These data records were, however, incomplete, as there were missing values for the other five parameters, which occurred completely at random within the data array. Details of the wastewater sampling and analyses, including descriptions of the wastewater quality and operational parameters are presented in Dong et al. (2011) and Dzakpasu et al. (2014). The MRP concentrations were measured according to the ascorbic acid method (HACH Method 8048), using kits supplied by HACH Lange (HACH Company, Loveland, CO., USA). The phosphorus removal performance of the ICW system is presented in detail elsewhere (Dzakpasu et al., 2015a, b).

2.3.2 Data pre-treatment

For any modelling strategy, the quality of the outputs strongly depends on the quality of the selected input variables. Therefore, data pre-treatment provides essential techniques on how measured data sets can be validated, including how the quality of the data can be improved. This is necessary to obtain reliable analyses results. Miller (2006) suggested the use of pre-processing techniques to deal with the noise in data sets by replacing the missing values and omitting the outliers to improve the data quality and the performance of ANFIS.

In the present study, all measurements were examined with respect to missing data, and values were replaced by values representing averages of adjacent data points. Furthermore, possible outliers and erroneous values were manually labelled. When identified, all outliers and erroneous values were, subsequently, removed from the data set and treated as missing values.

2.3.3 Selection of model input variables

The number of input variables selected for predicting the target output variables was dependent on their goodness of correlation. The coefficients were in the order: ORP (0.47)>EC (0.45)>pH (−0.17)>DO (−0.33)>T (−0.58). Overall, the correlation coefficient with absolute values greater than 0.3, between an input variable and the output variable was assumed to indicate a significant goodness of correlation (Mukaka, 2012) and consequently, selected as a predictor of the output. Based on this assumption, three models were constructed using different combinations of predictor variables (Table 2).

For each model, the available pre-processed data records were divided into three subsets, a training set, a checking set to ensure that models do not overfit the training data, and a testing set for validating the models.

Table 2 Optimal final architecture and performance of ANFIS models

		Model-01	Model-02	Model-03
Input variables		T[a], ORP[b]	T[a], ORP[b], EC[c]	T[a], ORP[b], EC[c], DO[d]
No. of nodes in input layers		2	3	4
No. of nodes in output layer		1	1	1
Shape of membership functions		bellmf	gaussmf	gaussmf
No. of membership functions		4	3	3
No. of fuzzy rules		16	27	81
No. of data pairs	training	59	59	59
	testing	59	59	59
MASE[e]	training	0.57	0.34	0.02
	testing	0.89	0.61	0.12

Note: [a]Temperature; [b]Oxidation-reduction potential; [c]Electrical conductivity; [d]Dissolved oxygen; [e]Mean absolute scaled error

2.3.4 Development of the ANFIS models

The ANFIS models were built by the *anfisedit* function in MATLAB®. The types and number of MFs in each ANFIS, including Gaussian curve, generalized bell curve, triangular and trapezoidal shaped functions, and the parameters were tested to determine an appropriate ANFIS model. The criteria for selecting the best final architecture were based on the error values between the model output values and the actual measured values. Table 2 presents the final architectures of the ANFIS models after many trials.

When the initial values of premise parameters and the architecture of the predictive models were defined, the hybrid learning algorithm trained the networks. Subsequently, the premise and consequent parameters of the network were pruned, and MFs of the variables were optimised. The models were then used for predicting effluent MRP concentrations.

2.3.5 Models performance evaluation criteria

Once the model structure had been selected, and the ANFIS network trained; the accuracy of the selected models was evaluated. The evaluation criteria considered in the present study was mean absolute scaled error (Hyndman and Koehler, 2006) and time series plots.

2.3.6 Computer Software

The ANFIS models were implemented with the Fuzzy Logic Toolbox™ (version 2.2.16, release 2012b) developed for MATLAB® version 8, release 2012b (The MathWorks, Inc., Natick, MA). All supporting statistical analyses were conducted using the Statistics Toolbox™ and various functions in MATLAB®. The Fuzzy Logic Toolbox™ provides MATLAB® functions, graphical tools, and a Simulink® block for analysing, designing, and simulating systems based on fuzzy logic. Their consistent methodology and modular organisation provide a flexible framework for experimentation and simplify customisation.

3. RESULTS AND DISCUSSION

3.1 Impact of selected input variables on effluent MRP concentrations

After the models had been trained, the inferences were performed in accordance with the linguistic fuzzy rules pertaining to each model. These rules were obtained after the network structures were selected. Defuzzified values for output variables were derived by changing input values manually in the interface. Different output values can be obtained from the 'Rule Viewer' according to the given input values. In addition to the defuzzified results, graphical outputs of the relations between input variables and the output can be derived; where two- or three-dimensional graphical outputs of all variables can be plotted and compared. Fig. 3 illustrates the three-dimensional graphical outputs indicating the impact of the selected input variables on the concentrations of MRP in the ICW effluent as screenshots of the Surface Viewer obtained from the ANFIS models after training.

The ANFIS models highlighted the importance of T, pH, DO, ORP and EC for the removal of MRP in ICW systems. Overall, low effluent MRP concentrations were found to be associated with a high T, a low ORP, a high EC, and a high DO. Due to the range of values recorded in this study (6.8-7.9), the impact of pH on MRP removal was not apparent. More specifically, at high EC (>800 μS/cm), DO (>4 mg/L), T (>14˚C), and ORP (<-0.5); MRP concentrations of less than 0.1 mg/L were recorded. On the other hand, at ORP (>-0.5), T (<4˚C) and EC (<400 μS/cm), effluent MRP concentrations were higher (>2 mg/L) and highly variable. Thus, the MRP effluent concentrations seemed to be highly influenced by salinity, oxidation and reduction conditions and water temperature.

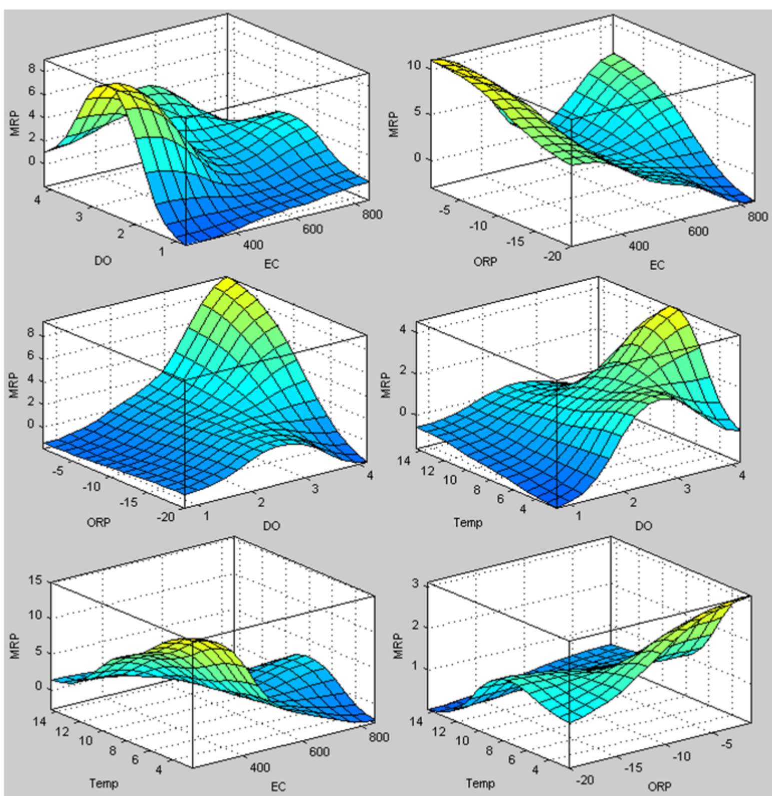

Figure 3 Three-dimension response surface graphs for ANFIS models

The apparent association between temperature and the removal of MRP conforms to observations from previous analyses (Akratos and Tsihrintzis, 2007). The dependency on temperature is mainly caused by plant decomposition and the return of P in organic form and P release from the precipitates (Kadlec and Knight, 1996).

DO and ORP are closely related parameters and their effect on P removal in the ICW was clearly complemented by previous observations. For example, it has been shown that the sorption behaviour of P is sensitive to ORP and that a low ORP (Braskerud et al., 2005) and low DO concentrations (Golterman, 1995; Maine et al., 2007) can cause the release of accumulated P from the sediment, causing an increase of MRP. Additionally, reducing conditions (i.e., lack of oxygen, DO concentrations below 0.1 mg/L) causes the solubilization of minerals and release of dissolved P (Kadlec and Knight, 1996). According to Jia et al. (2013), under low DO conditions, polyphosphate accumulating organisms take up organic substrates and store them as polyhydroxyalkanoates using the energy obtained partly from the glycogen utilization but mostly from the hydrolysis of the intracellular stored polyphosphate, resulting in orthophosphate release into solution.

Furthermore, some phosphate-accumulating microorganisms (e.g. phosphatase) are sensitive to high salinity (Scholz, 2006); a high concentration thus, suppresses their activities (Rejmánková and Sirová, 2007) and hence, the phosphorus treatment. In evaluating the nutrient removal performance of a constructed wetland using an SOM model, Zhang et al. (2008) reported that the high correlation of chloride and conductivity with MRP indicated that increased salt concentrations had adverse effects on MRP removal.

3.2 Optimal ANFIS architecture

The final architectures of the ANFIS models are given in Table 2. With different input variables, ANFIS models had generalized bell-shaped (Model-01) and Gaussian curve (Model-02 and Model-03) MFs giving the best results. The numbers of MFs for each of the input variables in Model-01, Model-02 and Model-03, were 4, 3, and 3, respectively. For each model, the numbers of training epochs were 120, which were determined by the error values between the model output values and the actual measured values. The numbers of fuzzy rules in the ANFIS models, which showed the highest accuracy, are also provided in Table 2.

3.3 Simulation of effluent MRP concentrations

After evaluating the three models, Model-03 was chosen to predict the MRP concentrations in the ICW effluent due to its lower MASE compared to the other two models, which indicated a relatively high accuracy in prediction. Fig. 4 and Fig. 5 depict the prediction results of MRP concentrations in the ICW effluent using Model-03. Fig. 4 shows a comparison between the model output and the actual measured data points during training, whereas Fig. 5 shows the performance of the model during validation when presented with previously unseen data. During the training, average MASE between the predicted and observed concentrations of MRP in the ICW effluent was 0.02. During the validation, MASE recorded between the predicted and observed concentrations of MRP in the ICW effluent was 0.12.

Overall, the ANFIS model performed very well in predicting the MRP concentrations in the ICW effluent with relatively higher accuracy. The recorded MASE was found to be higher than other AI models applied for modelling MRP concentrations in CW effluents. For example, in a mesocosm scale study, Dong et al. (2012) obtained MASE of 0.65 for predicting MRP using a Kohonen SOM model. Similarly, Li et al. (2014) obtained MASE of 8.23 and 4.07 respectively for ANN-based MLP and RBF in a horizontal subsurface wetland. On the other hand, Zhang et al. (2008) recorded of a much lower MASE of 0.048 for an ANN-based SOM model developed to predict MRP concentrations in the effluent of a CW system treating farmyard runoff.

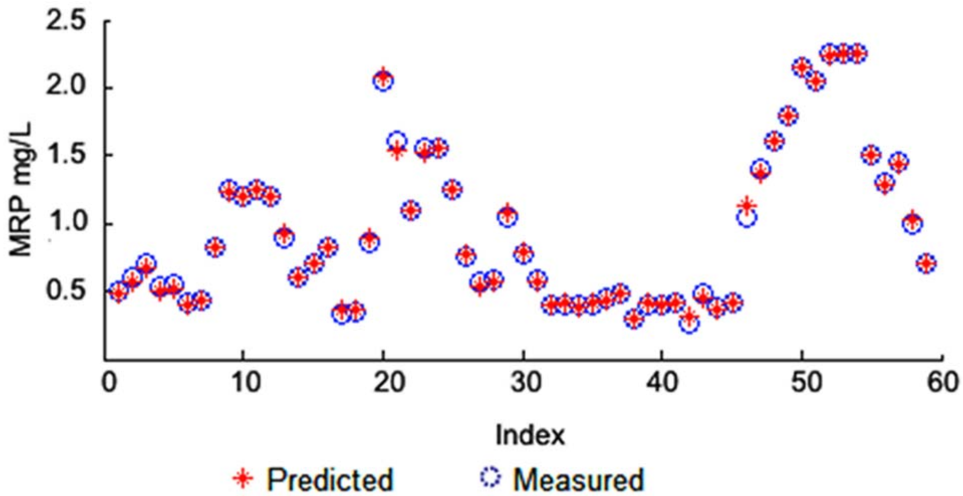

Figure 4 Performance of ANFIS model in predicting MRP concentrations in ICW effluent during training

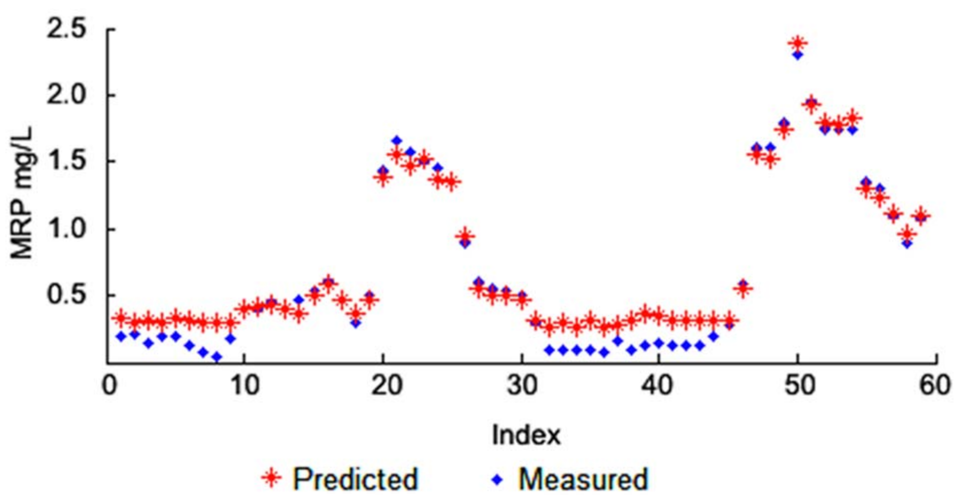

Figure 5 Performance of ANFIS model in predicting MRP concentrations in ICW effluent during validation

CONCLUSIONS

The removal of MRP in ICW systems was estimated with ANFIS models using simple, cost-effective and easy to measure physicochemical parameters as the sole predictors. Findings show that ANFIS could predict the effluent MRP variation quite strongly. The simulated effluent MRP concentrations well fit measured concentrations, which were predicted to a reasonable accuracy (MASE = 0.12). The models also emphasized the importance of physicochemical parameters in the removal of MRP in ICW systems. Thus, effluent concentrations of MRP could be predicted relatively accurately by other effluent water quality parameters, which can be measured quickly within few hours and cost-effectively. The validated model could be a useful tool for the rapid estimation of MRP removal in ICW systems. The rapid predictions with ANFIS provides an alternative to laborious laboratory analyses and serve as a management tool for day-to-day process control of ICW systems.

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