APPLICATION OF ARTIFICIAL NEURAL NETWORK IN HORIZONTAL SUBSURFACE FLOW CONSTRUCTED WETLAND FOR NUTRIENT REMOVAL PREDICTION

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Abstract. The aim of this study is to determine the appropriateness of the field measurements for the effectiveness of nutrients removal of *Phragmites australis* (Cav.) Trin. Ex. Steudel by applying artificial neural network (ANN) and also evaluate the removal capacity of LECA (light expanded clay aggregate) in a horizontal subsurface flow constructed wetland (SSFW). Two laboratory scale reactors were operated with weak and strong synthetic domestic wastewater continuously. One unit was planted with *P. australis* and the other unit remained unplanted (control reactor). The best performance was achieved with strong domestic wastewater treatment, the average removal efficiencies obtained from the evaluation of the system were 70.15% and 65.29% for TN, 66% and 57.4% for NH_4-N, 61.64% and 67.37% for TP and, 66.52% and 51.7% for OP in planted and unplanted reactors, respectively. The average NO_3^- concentration was 0.90 mg l^{-1} in the influent and 0.47 mg l^{-1} and 0.60 mg l^{-1} from planted and unplanted reactors, respectively. The average NO_2^- concentration was 0.80 mg l^{-1} in the influent and 0.56 mg l-1 and 0.88 mg l^{-1} from planted and unplanted reactors, respectively. Based on the obtained results, this system has potential to be an applicable system to treat strong domestic wastewater. The data obtained in this study was assessed using NeuroSolutions 5.06 model. Each sample was characterized using eight independent variables (hydraulic retention time (HRT), dissolved oxygen (DO), pH, temperature (T), ammonium- nitrogen (NH_4-N), nitrate (NO_3^-), nitrite (NO_2^-), ortho-phosphate (OP), and two dependent variable (total nitrogen (TN) and total phosphorus (TP)). The correlation coefficients between the neural network estimates and field measurements were as high as 0.9463 and 0.9161 for TN and TP, respectively. The results indicated that the adopted Levenberg–Marquardt back-propagation algorithm yields satisfactory estimates with acceptably low MSE values. Besides, the support matrix may play an important role in the system. The constructed wetland planted with *P. australis* and with LECA as a support matrix may be a good option to encourage and promote the prevention of environmental pollution.
Keywords: *artificial neural networks, constructed wetlands, LECA, Levenberg-Marquardt algorithm, Phragmites australis, wastewater treatment*

Introduction

Constructed wetlands are potentially low-cost solution for treating domestic and industrial wastewater in developing countries (Dordio et al., 2010). The use of wetland technologies is increasingly used for wastewater treatment because of the positive greenhouse results and the relatively low-cost and energy efficiency (Iamchaturapatra, et al., 2007; Gikas and Tsihrintzis, 2012). The performance of constructed wetlands is often correlated with its design, dimension and substrates used. The role of plants is also equally important (Vymazal, 2009). It is feasible to treat domestic wastewater in small rural communities using constructed wetlands. These systems are particularly valuable for on-site wastewater treatment in developing countries because they involve simple

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technology and the costs of construction and operation are low (Denny, 1997; Jones and Freeman, 2003). The production of vegetation biomass from treatment wetlands can provide economic returns to communities upon harvest. These economic benefits can be realized through production of “bio-gas”, animal feed, compost, and fiber to make paper (Belmont and Metcalfe, 2003).

Nitrogen removal is achieved, not only by bacteria, but also by plant uptake, adsorption, where ionized ammonia reacts with the media in horizontal subsurface flow (HSF) constructed wetlands (Kadlec and Knight, 1996; Yang et al., 2001; Al-Omari and Fayyad, 2003; Akratos and Tsihrintzis, 2007; Akratos et al., 2007). Phosphorus removal in horizontal subsurface flow (HSF) constructed wetlands (CWs) is a result of bacteria removal, plant uptake, adsorption by the porous media, and precipitation, where phosphorus reacts with the porous media and with minerals such as ferric oxyhydroxide and carbonate (Kadlec and Knight, 1996; Yang et al., 2001; Akratos and Tsihrintzis, 2007). Bacteria removal and plant uptake are responsible for ortho-phosphate removal, while precipitation and adsorption are responsible for the removal of all phosphorus forms (Akratos et al., 2009).

Phragmites australis (Cav.) Trin. Ex. Steudel was used for the system. It is also known as common reed, is a perennial, wetland grass that can grow to 15 feet in height. The invasive variety of *P. australis* creates tall, dense stands which degrade wetlands and coastal areas by crowding out native plants and animals, blocking shoreline views, reducing access for swimming, fishing, and hunting and can create fire hazards from dry plant material. It spreads rapidly due to its vigorous rhizomes (horizontal roots that produce new shoots), grow more than six feet per year.

The limitations of traditional gravel substrate fostered the exploration of employing alternative support media in wetland systems, for enhancing their treatment performance (Saeed and Sun, 2011). .Previous studies have shown that LECA is capable to remove by sorption for subsurface flow wetlands. At the same time, constructed wetland systems based on LECA have the benefits of good water conductivity, which lower the risk of clogging, and low heat conductivity, which makes them preferable in cold climate conditions and, in the case of high Ca and Mg content, also a high phosphorus adsorption capacity (Nurk et al., 2009). In addition it has a pH buffer capability near neutral conditions (pH ~ 7-8) and a good control of hydraulic permeability which makes it an appropriate medium for plant growth. (Dordio et al., 2007).

Until now, the majority of the models on constructed wetlands are focused on input–output data and the production of either linear regression equations or first order decay models (Akratos et al., 2008). To these authors’ knowledge, there are no publications studying the applicability of ANNs in the prediction of nutrient removal in constructed wetlands. The present study follows a different approach in modeling nutrient removal in CWs. The aim is to examine whether artificial neural networks (ANNs) could be used in prediction of nutrient removal in horizontal subsurface flow constructed wetlands, and if so, to suggest an appropriate topology (that is, input variables, number of ANN neurons, etc.) for a successful ANN. The data used to train and test the ANNs were collected in pilot-scale horizontal subsurface flow constructed wetlands. With this in mind, we have designed, constructed and operated laboratory scale subsurface constructed wetlands receiving synthetic weak and strong domestic wastewater. LECA based subsurface horizontal flow constructed wetland planted with *P. australis*. Main goals were to investigate the effectiveness of *P. australis* and evaluate the removal

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capacity of LECA (light expanded clay aggregate) in a subsurface flow wetland (SSFW) to remove TN, NH_4-N, NO_3^-, NO_2^-, TP and OP levels. The results obtained will yield insights about the actual application of the system and also promote the prevention of environmental pollution.

Material and Methods

Experimental set-up and operating conditions of CW

CW units were operated in subsurface horizontal flow mode, where all influent wastewater was made to flow through the CW beds, and no wastewater flowed above the CW beds. This type of CW is called subsurface-flow constructed wetland or SSCW (Sawaittayothin and Polprasert, 2006).

Two pilot-scale SSCW units, made from stainless steel, and each with dimensions of 0.2x2.45x0.45 m (width x length x depth). LECA was used as the support media in these units at a depth of 27 cm. These two pilot-scale SFCWs were operated in parallel, one as an experimental unit and the other as a control. *P. australis* were planted at a density of 4 m^{-2} (USEPA, 1988). Hydraulic retention time of the system was 3 d. The treatment system received synthetic domestic wastewater which was prepared according to OECD (OECD, 1984). Wastewater influent values were set by making dilution. As a priority weak domestic wastewater (COD~250 mg l^{-1}) and for the next step strong domestic wastewater (COD~500 mg l^{-1}) (Erdoğan et al., 2005) was applied and the system run stably. Wastewater was fed continuously to the SFCW units to acclimatize the soil microbes and support growth of the *P. australis* plants.

All physical, chemical and biological parameters of the wastewater were analyzed according to Standard Methods (APHA, 2005).

Analytical methods

The pH, temperature, dissolved oxygen (DO), total nitrogen (TN), ammonium-nitrogen (NH_4-N), nitrate (NO_3^-), nitrite (NO_2^-), total phosphorus (TP) and ortho-phosphate (OP) of the influent and effluent were measured. The pH, temperature and DO were measured by a Consort multi-parameter analyzer. Other analyses were performed with measurement kits and analyzed in a Hach-Lange DR5000. All analyses were done in triplicate.

Support media (light expanded clay aggregate-LECA)

Natural lightweight aggregates are industrial raw materials showing usually formed as a product of volcanic porous and large mass distributions. Industrially produced synthetic aggregates, as they have a wide variety of products generally known by the trade names.

The sintering process occurs rapidly, where the specific volume increases at temperatures between 1100-1300°C for clay and shale, generally called swellable clays. Raw materials for expanded clays that are widely used include early sintered clay, sandy clay and shale. The top of the outer surface of sintered porous ceramic products are slightly hard and have a piroplastic structure consisting of a shell. This lightweight aggregate material formation in the construction industry is evaluated by light extraction structure elements (Gündüz et al., 2006).

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Artificial neural network (ANN) software

ANN is a technique inspired by biological neuron processing. It has a wide application field on several sciences for time series forecasting, pattern recognition and process control. Its main advantage over traditional methods is that it does not require the complex nature of the underlying process (Nayak et al., 2006). The principal drawback of ANNs is that they are typically used as a “black-box” approach, hiding the physics of the modeled process; in the present work, however, a model, inspired from the ANN response curves to the input parameters, is proposed as an alternative to the ANNs. This model successfully describes their complex dynamics. There are many types of networks for an ANN application and the selection of the proper type depends on the nature of the problem and data availability. The multi-layer perception (MLP) is perhaps the most popular network used in hydrological modeling (Govindaraju, 2000a, Govindaraju, 2000b). In MLP, the artificial neurons, or processing units, are arranged in a layered configuration containing an input layer, a processing (“hidden”) layer (in complex topologies two hidden layers are used) and an output layer.

An artificial neural network (ANN) is a computational structure inspired by the study of biological neural processing (Rao, 1995). ANN is a data modeling tool that is capable of capturing and representing complex relationships between inputs and outputs. Its instants are composed of large numbers of highly interconnected processing elements, which are called ‘‘neurons’’ and are tied together with weighted connections. Each neuron works as an independent processing element and has an associated transfer function, which describes how the weighted sum of its inputs is converted to the results into an output value. Each hidden or output neuron receives a number of weighted input signals from each of the units of the preceding layer and generates only one output value (Elhatip and Komur, 2008).

The MLP networks are an extension of perceptron networks in that they have one or more hidden layers. Each neuron computes a weighted sum of all incoming signals and after adding a threshold value produces the argument to the transfer function which generates the output of a neuron. The backpropagation algorithm which involves two phases is usually used for tainting MLP networks. During the first phase or feed-forward phase, the free parameters of network do not change, and the information of inputs is propagated through the network layer by layer. At the end of this phase value for network error is computed which represents the difference between the desired response and the output produced by the network in response to the presented input vector. During the second phase or backward phase, free parameters of network (weights and biases) are adjusted to minimize the error of network which is calculated according to an error measure. Although the MLP networks can have more that one hidden layer, theoretical works have shown that provided sufficient number of neurons, a network with only one hidden layer can approximate any complex nonlinear function (Cybenko, 1989; Hornik et al., 1989; Talebizadeh and Moridnejad, 2000).

In this study, different MLP networks with one single layer and Log-Sigmoid as the transfer function were used for forecasting lake levels. It is shown that the incorporation of Levenberg-Marquardt algorithm into backpropagation algorithm speeds up the process of convergence (Hagan and Menjah, 1994), therefore we used this algorithm for training the networks. The adequacy of the ANN is evaluated by considering the coefficient of determination (R^2), also the values of root mean square error (RMSE), normal root mean square error (NRMSE), mean absolute error (MAE) and Normal mean absolute error (NMAE) are used as the index to check the ability of model

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(Coulibaly et al., 2001; Kumar et al., 2002; Coppola et al., 2003; Asghari Moghaddam, 2006; Maedeh et al., 2013).

ANN (NeuroSolutions 5.06, NeuroDimension, Inc., Gainesville, Florida) was implemented on experimental output. All data were tested 20 times with the ANN program. These 20 solutions were repeated 100 times each, and every 100 groups were confirmed 3 times in the NeuroSolutions 5.06 program.

Results and Discussion

Performance Results of Nutrient Removal

In weak domestic wastewater treatment, the temperature values were 24.9 ºC in the influent and 26.5 ºC for the effluent of planted and unplanted reactors. In strong domestic wastewater treatment system, the temperature values were 24.5 ºC for the influent and 25.7 ºC for the effluent of planted and unplanted reactors. For *P. australis* the optimum temperature range was 6-25 ºC (USEPA, 1993). Both for weak and strong wastewater treatment temperature changes showed appropriate development range for *P. australis*.

In weak domestic wastewater treatment, the pH values were 8.0 for the influent and 8.08 and 8.3 for the effluent of planted and unplanted reactor, respectively. In strong wastewater treatment system, the pH values were 8.02 for the influent and 8.11 and 8.28 for the planted and unplanted reactor, respectively. For bacteriological removal of nutrients, a nitrification pH greater than 6.6 and a denitrification pH between 6.5 to 9.5 is ideal (Cossu et al., 2001). Thus, the measured system pH values provide favorable conditions for nitrification and denitrification.

pH of the rhizosphere which was the nitrogen source used, largely affected by weeds because it is large quantities of food, or a cation (ammonium) or an anion (nitrate) is caused by the absorption, in subsurface flow wetlands. The roots must remain electrically neutral. When plants absorb anions greater than cation (ammonium basic nitrogen source) the proton is released too much, it reduces the pH. Nitrate is the main nitrogen source would tend to increase the pH (Vymazal and Kröpfelova, 2008). In this study, the measured pH higher values of the effluent of the planted and unplanted reactor suggest that this system is used nitrate as the source of nitrogen base.

In the weak domestic wastewater treatment, the EC values were 708 µS/cm for the influent, 1215 µS/cm for the planted reactor and 847 µS/cm for the unplanted reactor. In the strong wastewater treatment system, the EC values were 721 µS/cm for the influent, 1238 µS/cm for the planted reactor and 828 µS/cm for the unplanted reactor. The results of high electrical conductivity show that a wide range of mineral ions exists in wastewater (El-Kheir et al., 2007).

DO values were 2.12 mg/l for the influent, 1.74 mg/l for the planted reactor and 2,01 mg/l for the unplanted reactor in the weak domestic wastewater treatment,. In the strong wastewater treatment system, the DO values were 2.01 mg/l for the influent, 0.77 mg/l for the planted reactor and 1.05 mg/l for the unplanted reactor. The results of high electrical conductivity show that a wide range of mineral ions exists in wastewater (El-Kheir et al., 2007). According to Henry's Law water dissolved oxygen concentration is inversely proportional to the temperature of the water (Dağlı, 2006). In line with this view, the period in which the weak and strong domestic waste water treatment, reduction in dissolved oxygen levels are observed with increasing temperature. Subsurface flow wetlands have low dissolved oxygen in the system, consisting of high temperature, high oxygen requirement for the oxidation of carbon compounds and can be explained by the continuous operation of the system. Subsurface flow wetlands have low dissolved oxygen in the system. It can be explained by consisting of high temperature, high oxygen requirement for the oxidation of carbon compounds and the continuous operation of the system.

Nutrient removal

High levels of N and P are known to natural water bodies and cause eutrophication. Nutrients generally (N, P) accumulate in the plant biomass and are removed through harvesting (Gregory, 1999). Nitrogen and P losses can be attributed to uptake by weeds that become attached to biofilm, which is attached to the walls of the systems, and sedimentation of particular forms of N and P (Körner et al., 2003).

Total Nitrogen (TN)

Nitrogen (N) is a major component in municipal wastewater, storm water runoff from urban and agricultural lands, and wastewater from various types of industrial processes (DeBusk, 1999; Abou-Elela et al., 2013). Nitrogen can exist in various forms in water, such as particulate and dissolved organic N, ammonium, nitrite, and nitrate. These various forms can transform and serve as sources or end products for each other within the nitrogen cycle (Dotch and Gerald, 1995; Abou-Elela et al., 2013). For this reason, only TN is considered. Although nitrogen components can be affected by various processes, denitrification is the only major net, high-term removal process for TN.

Figure 1 shows the TN concentration in the influent and effluent of the planted and unplanted reactor. TN removal efficiencies in the weak domestic wastewater treatment for the planted and unplanted reactors were 83.95% and 66.8%, respectively. In the strong wastewater treatment removal efficiencies were lower, which were 70.15% and 65.29% for planted and unplanted reactors, respectively.

Compared in terms of TN, vegetation removal systems are an important advantage compared with unplanted systems. Being part of the surface area that contributes to the wetland plant nutrient unit quantities, the types of plants that can be used is limited depending on the type and environmental conditions. According to comparative measurements of the planted and unplanted systems, planted systems between 3-19% more go to TN supply (Tanner et al., 1995). Comparing the data obtained from the unplanted (control) reactor compared with that of the planted reactor, the plants' role in removing nitrogen from the subsurface flow wetland ranged from 4.86 to 17.15%.

P. australis is an effective biological purifier in a subsurface flow wetland where *P. australis* used in both strong and weak wastewater application results in high speed growth. In a subsurface flow wetland system, it is thought that the low dissolved oxygen (DO) amount restricts the nitrification process. The TN removal mechanism is thought to be an active denitrification system.

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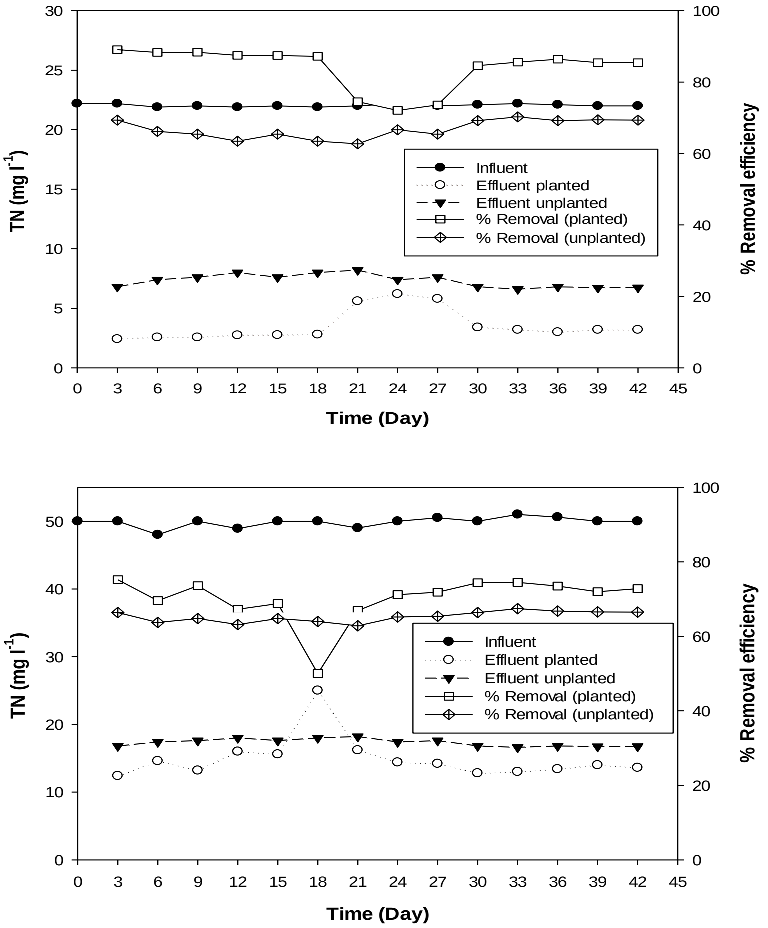

Figure 1. *Removal efficiencies and TN concentrations in the planted and unplanted reactors treated with (a) weak domestic wastewater and (b) strong domestic wastewater.*

Ammonia Nitrogen (NH4-N)

The average NH_4-N concentrations in the weak domestic wastewater treatment were 0.63 mg l^{-1} in the influent, 0.08 mg l^{-1} in the planted and 0.09 mg l^{-1} in the unplanted reactors (*Figure 2*). In weak domestic wastewater treatment NH_4-N concentrations were 6.18 mg l^{-1} in the influent, 2.10 mg l^{-1} in the planted and 2.63 mg l^{-1} in the unplanted reactors. The NH_4-N removal efficiencies in the strong domestic wastewater treatment for the planted and unplanted reactors were 66% and 57.4%, respectively.

A subsurface flow system for weak domestic wastewater provides better NH_4-N removal than for a strong domestic wastewater application. The rest of the environment remaining in the subsurface flow artificial wetland system (benthic zone) tends to be devoid of oxygen. Generally due to the limited amount of available oxygen, biological nitrification of ammoniacal nitrogen removal is limited by the lack of oxygen at the end of the biological nitrification process because the ammonium nitrogen (NH_4-N) cannot perform the requested removal. For domestic wastewater in subsurface flow systems, wastewater output to low levels of ammonium nitrogen in a large wetland area requires long waiting periods (USEPA, 1993). In particular, the presence of dissolved oxygen in the environment around the root zone due to the decrease in pH indicates nitrification

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(Bezbaruah and Zhang, 2004). A control reactor plant that does not have a resource environment that provides oxygen, such as plant roots, leads to high pH values. The NH_4-N removal in the control reactor was low, which shows that there was less nitrification in the reactor.

Synthetic wastewater with *P. australis* was used and lab-scale horizontal flow wetland wastewater treatment systems was studied over a period of 10 months (Drizo et al., 1997). Almost all of the NH_4-N systems using vegetation and plant systems exhibited NH_4-N removal efficiencies within a range of 40-75%. In this study, similar to the weak domestic waste water reactors, the use of *P. australis* resulted in NH_4-N removal efficiencies between 57.4%-74.4%.

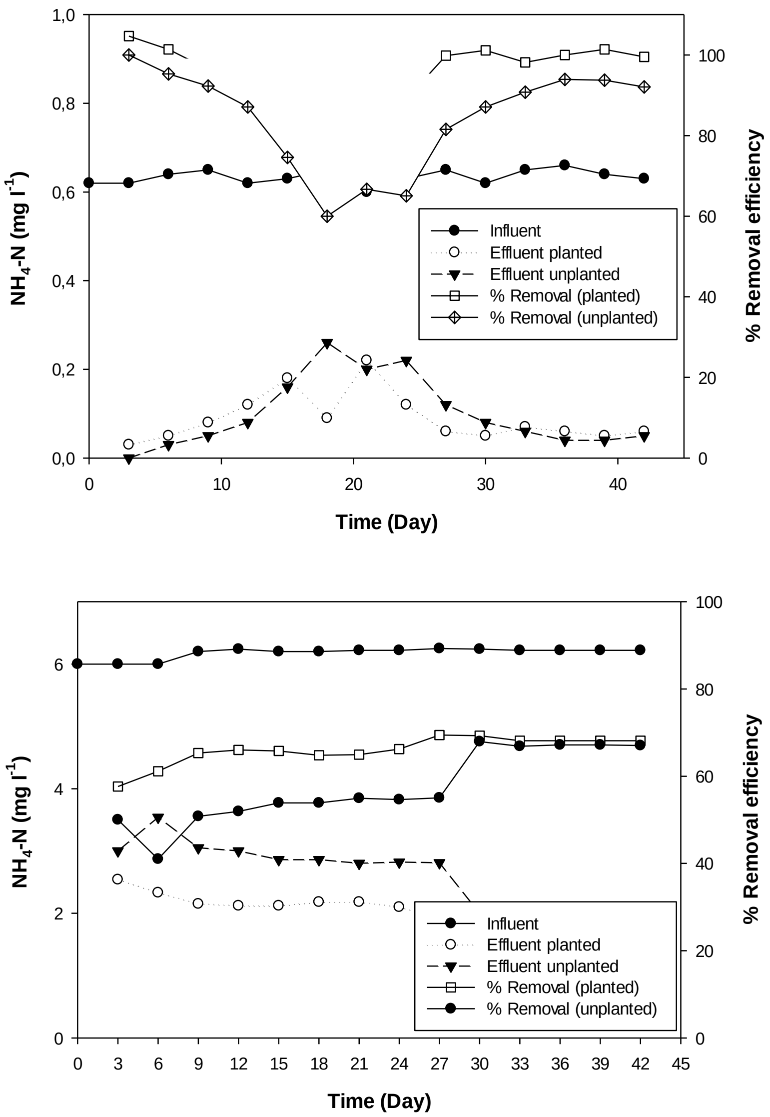

Figure 2. *Removal efficiencies and NH4-N concentrations in the planted and unplanted reactors treated with (a) weak domestic wastewater and (b) strong domestic wastewater.*

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Nitrate and Nitrite (NO_{3-} and NO_{2-})

Figures 3 and 4 show the NO_3^- and NO_2^- concentrations in the influent and effluent of the planted and unplanted reactor. Nitrate formed as a result of nitrification, is used for the transition denitrification and plant body (Akça et al., 1998).

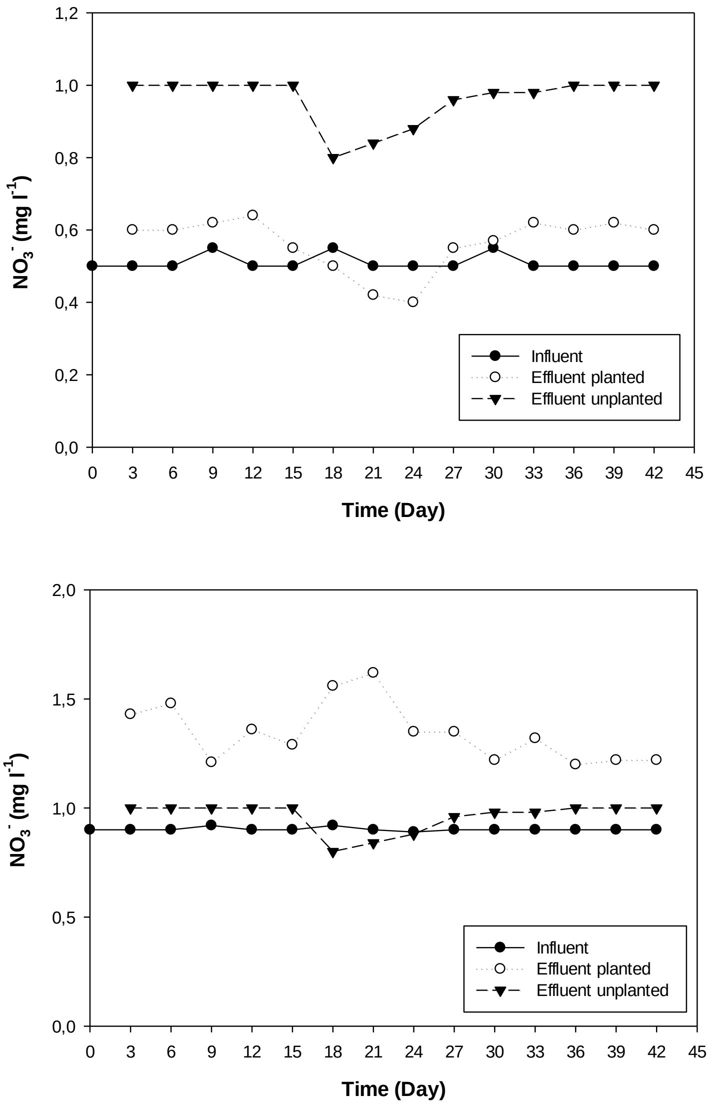

Figure 3. *Removal efficiciencies and NO_3^- concentrations in the planted and unplanted reactors treated with (a) weak domestic wastewater and (b) strong domestic wastewater.*

Nitrate is the most oxidized form of nitrogen in the wetlands (+5 oxidation) which is due to the oxidation state of nitrate nitrogen being chemically stable, and many energy-consuming biological transport processes will remain unchanged.

Nitrate is formed as a result of nitrification, denitrification and plant spent with the transition structure (Akça et al., 1998). As we have observed in practice, the weak domestic waste water nitrate concentration is generally greater than the nitrate concentration in the system output, which illustrates the fact that in the nitrification

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process, the optimum pH range is from 7.5 to 8.6 (Govindaraju, 2000b). The system meets this condition.

Nitrite (NO_2^-), has an oxidation state (+3) that is in between the oxidation states of ammonia nitrogen (-3) and nitrate (+5). Due to the energetic state of this medium, not much of the wetland is chemically stable, due to the extremely low concentrations of nitrite. Often, incomplete assimilation of nitrogen and nitrite levels in the wetlands indicates the presence of an anthropogenic nitrogen source (Crittenden et al., 2012).

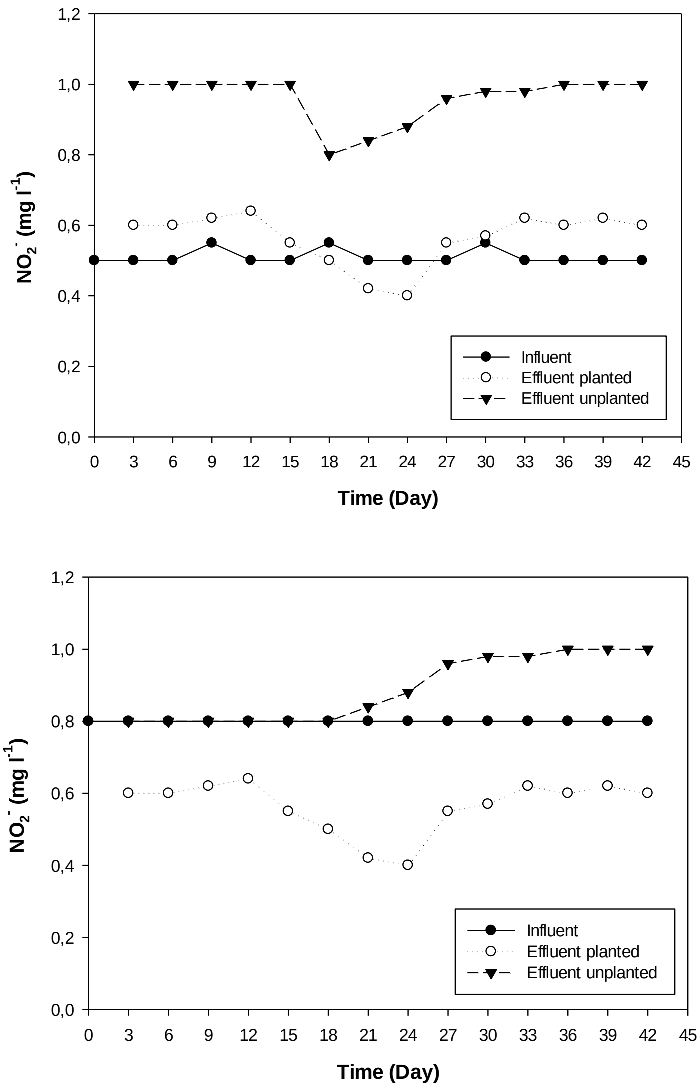

Figure 4. *Removal efficiencies and NO_2^- concentrations in the planted and unplanted reactors treated with (a) weak domestic wastewater and (b) strong domestic wastewater.*

Total Phosphorus (TP)

Phosphorus interacts strongly with wetland soils and biota, which provide both short-term and sustainable long-term storage of this nutrient (Kadlec, 2005). Phosphorus movement in wetlands is influenced by hydrologic, soil and biotic processes.

TP removal efficiencies in weak domestic wastewater treatment for the planted and unplanted reactors were 40.52% and 37.91%, respectively. In the strong wastewater

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treatment, removal efficiencies were 61.64% and 67.37% for the planted and unplanted reactors, respectively (*Figure 5*).

The phosphorus removal rate is site-specific depending on the wastewater characteristics, type of aquatic plant, harvest frequency, and climate. Typical removal rates vary between 30-50% (Sarıalioğlu, 2003). Average TP removal rates obtained in this study appears to be consistent with those reported in literature.

Phosphorus is one of the necessary elements for microorganisms' growth in water and is known as the primary nutrient that limits productivity. However, the most important phosphorus removal in constructed wetland systems is the adsorption of phosphates in the event of filler material (Tang et al., 2010). Using LECA as the study medium, the TP removal rates in the subsurface flow reactor control system for the weak and strong domestic waters were 37.91% and 67.37%, respectively, which confirms as in the literature suggests that phosphorus is absorbed by the media material.

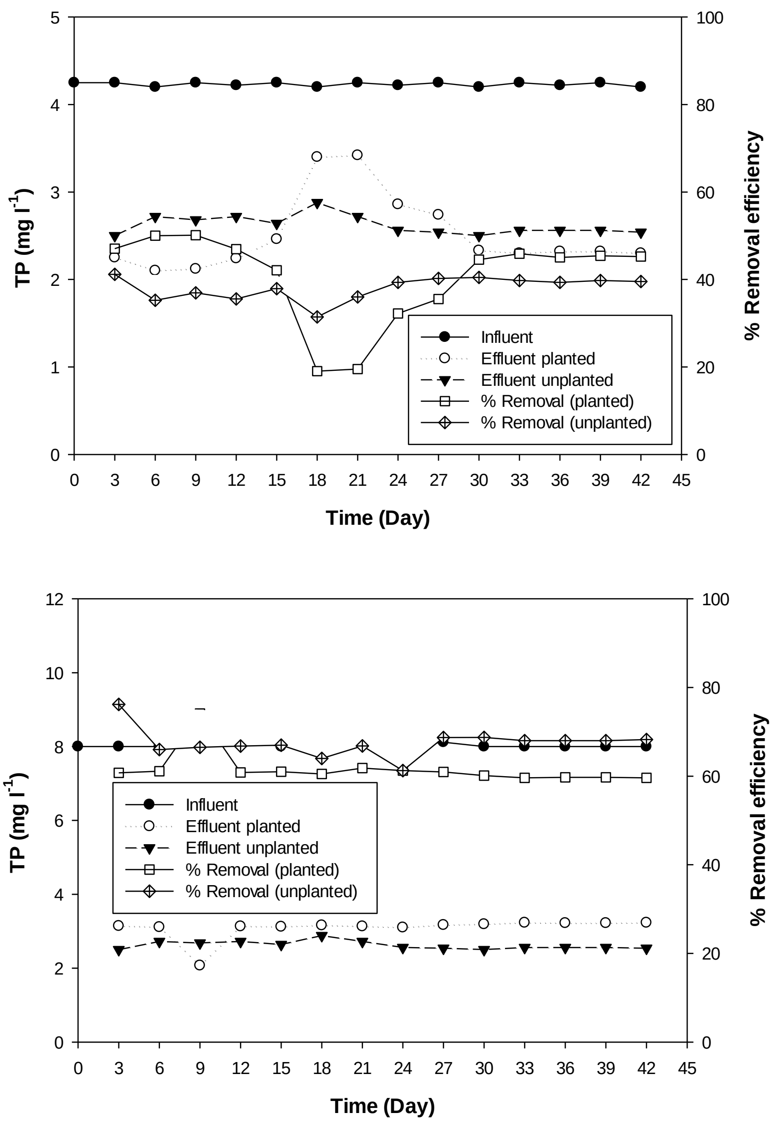

Figure 5. *Removal efficiencies and TP concentrations in the planted and unplanted reactors treated with (a) weak domestic wastewater and (b) strong domestic wastewater.*

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Ortho-phosphate (OP)

Ortho-phosphate is the most easily removed of the three types of phosphorus. Ortho-phosphate is the predominant inorganic form of P in surface waters. This form of P readily accumulates in wetland vegetation and soils, as a result of biological uptake and chemical bonding (Dotch and Gerald, 1995). The main OP removal mechanism in DWWT is plant uptake.

Figure 6 shows the OP concentration in the influent and effluent of the planted and unplanted reactor. OP removal efficiencies in the weak domestic wastewater treatment for the planted and unplanted reactors were 36.4% and 16%, respectively. In the strong wastewater treatment, removal efficiencies were greater, which were 66.52% and 51.7% for planted and unplanted reactors, respectively.

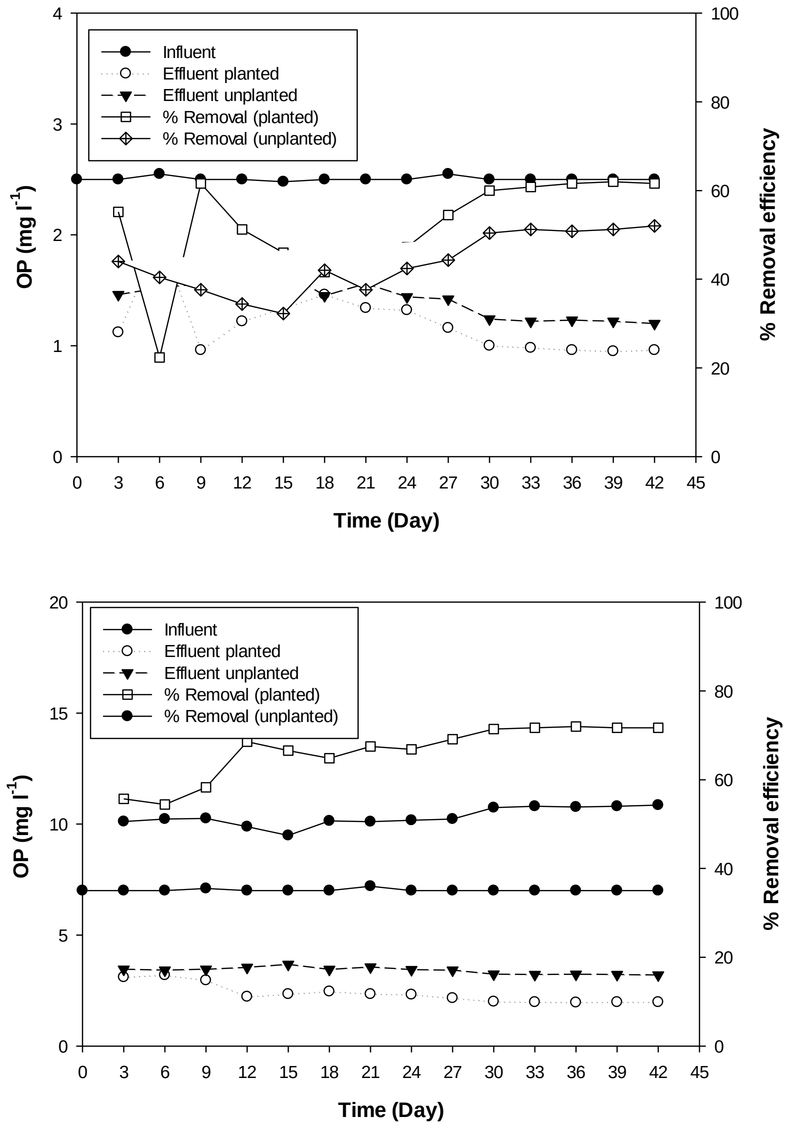

Figure 6. *Removal efficiencies and OP concentrations in the planted and unplanted reactors treated with (a) weak domestic wastewater and (b) strong domestic wastewater.*

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The predominant form of phosphorus in surface waters is orthophosphate. This form of phosphorus found in wetland plants and soil accumulate biological and chemical bonds by trading iron and aluminum phosphate minerals at low pH values with calcium phosphate minerals at high pH values. This is the primary phosphorus removal mechanism in the wetlands (Richardson, 1985). It was studied phosphorus removal using phosphorus filler articles in wastewater with Al, Fe, Ca^{+2} and found the formation of clay minerals and a complex adsorption, ion PO_4-P deposition process occurred at the same time as with the Fe, Al and Ca state, which is resolved by precipitation in the form of phosphates (Richardson, 1985; Dirim, 2006, Yılmaz, 2003). In this study, ortho-phosphate formed by calcium phosphate minerals is thought to be the basic mechanism.

To determine the appropriateness of the field measurements for evaluating performance of nutrient removal of *P. australis* in a horizontal subsurface flow wetland (SSFW), the ANN was applied.

Artificial Neural Network (ANN) Modelling Results

Application of ANN

Here, the produced ANN model architecture is a multi-layer, feed-forward and Levenberg–Marquardt back-propagation architecture. In general, a neural net, has a parallel interconnected structure consisting of (1) an input layer of neurons (independent variables), (2) a number of hidden layers, and (3) an output layer (dependent variables). The number of input and output neurons is determined by the nature of the problem. The hidden layers act as feature detectors, and in theory, there can be more than one hidden layer (Yonar and Yalili Kilic, 2014). The eight neurons in the input layer include hydraulic retention time (HRT), dissolved oxygen (DO), pH, temperature (T), ammonium- nitrogen (NH_4-N), nitrate (NO_3^-), nitrite (NO_2^-), ortho-phosphate (OP). The two neuron in the output layer indicate total nitrogen (TN) and total Phosphorus (TP) values (*Fig. 7*). Note that the number of hidden layers and number of neurons in this layer directly affect the performance of the network.

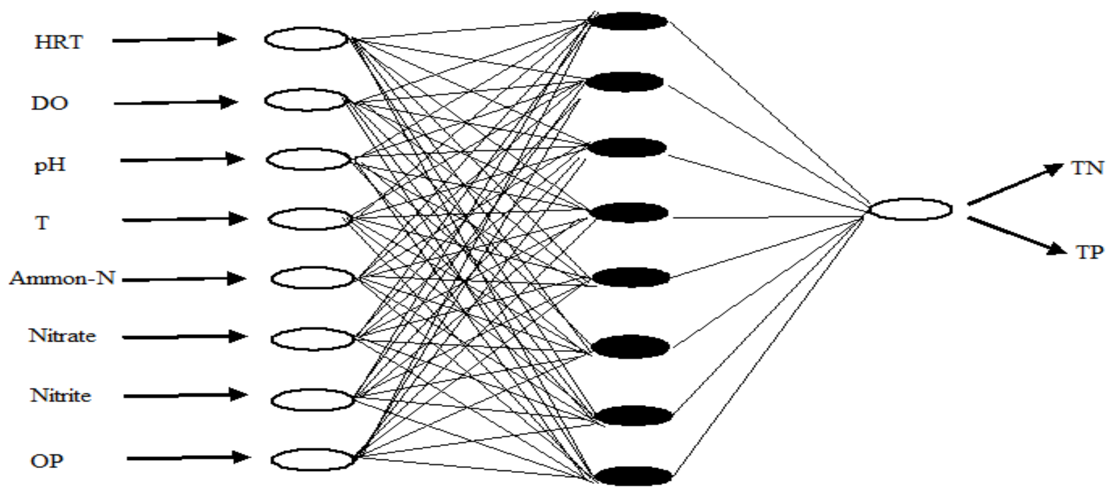

Figure 7. *Artificial neural networks (ANN) optimized structure.*

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In the artificial neural network (NeuroSolutions 5.06) in this study, all data were tested 20 times. The 20 obtained solutions were repeated 100 times each, and every 100 groups were confirmed 3 times in the NeuroSolutions 5.06 program. Both training values and cross-validation values are demonstrated in *Table 1*. With the validation complete, it can be observed that the standard deviation and application values resemble each other, which demonstrates that there was not high deviation. All data obtained as the result of calculations of the ANN are shown in *Figure 8*. The average mean square error (MSE) is shown in *Figure 9*.

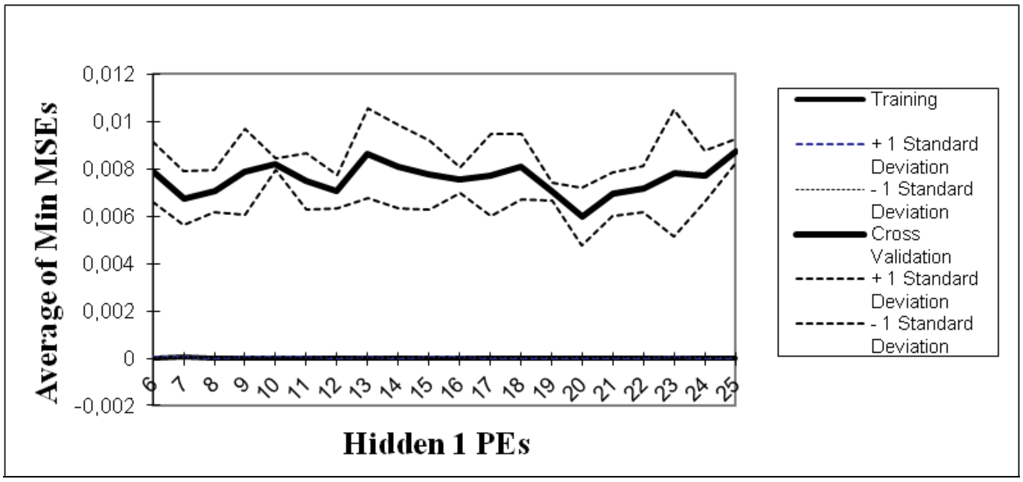

Figure 8. *Average mean square error (MSE) with standard deviation (PE = processing element).*

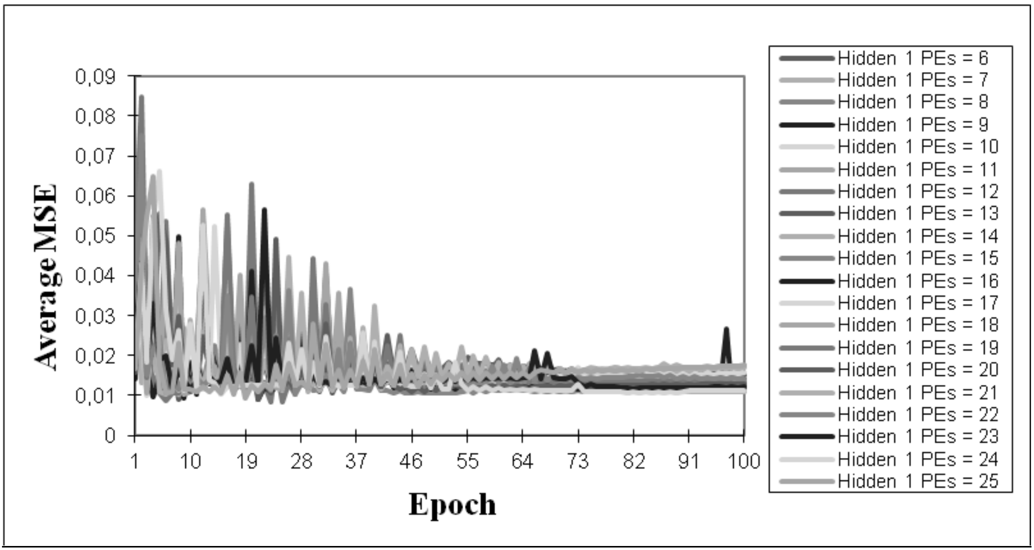

Figure 9. *Average cross-validation.*

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Table 1. *Results of the applied model (PE = processing element, MSE = mean square error)*

Best Networks	**Training**	**Cross-Validation**
Hidden 1 PEs	25	20
Run #	1	1
Epoch #	99	21
Minimum MSE	$2{,}53\text{x}10^{-7}$	0,00471296
Final MSE	$3{,}50\text{x}10^{-6}$	0,0014502613

Figure 10 shows a comparison between the calculated and experimental values of the output variable for the test sets, using the neural network model with 10 hidden layers. The software used two lines to show the success of the predictions. The one is a perfect fit (predicted data equal to experimental data), on which all data of an ideal model should lay. The other line is the line that best fits the data from the NeuroSolutions 5.06 program, and a perfect fit is obtained using a regression analysis based on the minimization of the squared errors. The correlation coefficients (r) of those lines are also presented in *Table 2*. In *Figure 10*, the TN and TP line has a correlation coefficient of 0.9463 and 0.9161, respectively for the test set. Simulations based on the ANN model were performed to predict the behavior of the system under different conditions. All of the studied parameters in this work have considerable effects on the TN and TP. The results confirm that neural network modeling can reproduce experimental data about the performance of the horizontal subsurface flow wetland, and the data are within the experimental ranges adopted in the model.

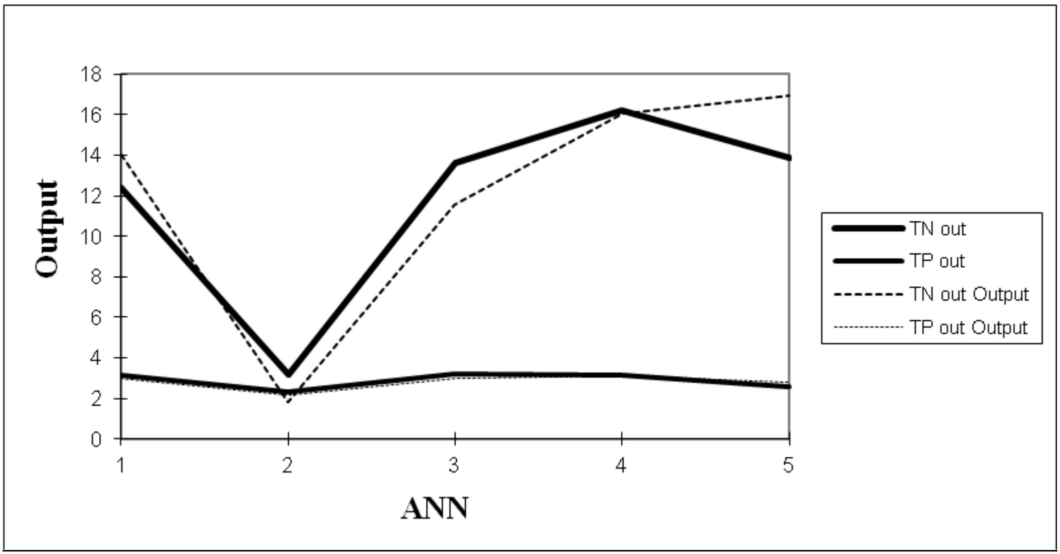

Figure 10. *Desired actual net outputs.*

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This study showed that ANN modelling approach can be utilized successfully and beneficially to evaluate the effectiveness of nutrient removal of *Phragmites australis* (Cav.) Trin. Ex. Steudel in in a horizontal subsurface flow wetland (SSFW). There have been no publications studying the applicability of ANNs in the prediction of nutrient removal in constructed wetlands. The results indicated that the adopted Levenberg–Marquardt back-propagation algorithm yields satisfactory estimates with acceptably low MSE values. ANN modelling approach yields estimates with high precision with r value of 0.9463 and 0.9161 for TN and TP, respectively if a suitable structure with sufficient number of neurons is selected.

Table 2. *Truth values (TN = total nitrogen, TP = total phosphorus, MSE = mean square error, NMSE = normalized mean square error, MAE = mean absolute error).*

Performance	TN	TP
MSE	3,605560003	0,025114
NMSE	0,177943383	0,19722624
MAE	1,646680728	0,14678872
Min Abs Error	0,137772698	0,034816049
Max Abs Error	3,051231654	0,196431697
r	0,946343962	0,91619751

Conclusion

Temperature is one of the main parameters affecting the system efficiency. The effluent values of the measured temperature values are appropriate for the development of the plant. During the study period, the pH values of the system provided favorable conditions for nitrification and denitrification processes.

LECA based subsurface horizontal flow constructed wetland planted with *P. australis* has shown an overall high efficiency to remove several typical pollutants present in synthetic domestic wastewater, namely TN, NH_4-N, NO_3^-, NO_2^-, TP and OP. Based on the data obtained from the subsurface flow reactor system, a comparison of the planted and unplanted reactors showed that system was effective in strong domestic wastewater treatment. The support media of LECA alone could be represented as the major responsible for the efficiency of pollutant removal, but the presence of vegetation in planted beds did contribute both in terms of efficiency as well as of the celerity of the process. LECA also showed the capacity to buffer the pH of wastewater to the range of neutrality or slight basicity, which contributes to its remarkable adequacy for the development of the plants and microorganisms. This type of alternative practice is a good option to encourage and promote the prevention of environmental pollution.

The calculated removal efficiencies were consistent during the experimental period. This type of wastewater treatment system would be successful because it can satisfactorily reduce the level of pollutants and be a source of acceptable irrigation water. Nonetheless, further studies should be carried out with a wider range of wastewaters and pollutant types. In addition, performances in full-scale systems and with other wastewater flow regimes should be assessed in order to confirm this solution as a viable option.

Artificial neural networks are able to model nutrient removal in horizontal subsurface flow constructed wetlands. Topologies of successful networks were suggested, and the network predictions were validated against an extended dataset reported here and a separate dataset compiled from studies published earlier. The performance of the networks was found to be reasonably good for wetland design purposes.

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