



Journal of Environmental Science and Technology

ISSN 1994-7887

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Aeration Control Based on a Neural Network in a Biological Aerated Filter for Simultaneous Removal of Ammonia and Manganese

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ABSTRACT

This study was conducted to monitor and control aeration by means of an online Neural Network (NN) of a Biological Aerated Filter (BAF). The BAF is an advanced drinking water treatment system equipped with Dissolved Oxygen (DO), oxidation-reduction potential, pH, ammonia and nitrate sensors. The main function of the BAF is to treat contaminated water by simultaneously reducing the levels of ammonia and manganese to below permit limits. Aeration was supplied to the BAF and controlled by a neural network. Real-time data was accurately predicted by the NN with errors below 5% for all sensors. The bending point was apparently created in DO neural network data when the simultaneous ammonia and manganese removals were below limits. The NN program detected the bending point and immediately stopped the aeration of the BAF. Hence, NN can optimize the aeration requirement and system performance, shorten time demand and reduce consumption of manpower and electricity.

Key words: Aeration, neural network, real-time monitoring, biological aerated filter, simultaneous ammonia and manganese removal

INTRODUCTION

More than one billion people around the world lack access to an improved water source (WHO., 2003). This is because the water is contaminated with a high number of pollutants such as organic carbon, nitrogen contents such as ammonia ($\text{NH}_4^+\text{-N}$), nitrite ($\text{NO}_2^-\text{-N}$) and nitrate ($\text{NO}_3^-\text{-N}$) and metals such as manganese (Mn^{2+}), aluminium (Al^{3+}), nickel (Ni^{2+}), zinc (Zn^{2+}) and lead (Pb^{2+}). The $\text{NH}_4^+\text{-N}$ produced from waste, sewage and garbage is a serious cause of water pollution (Hasan *et al.*, 2011a). In developing countries such as Malaysia, the presence of $\text{NH}_4^+\text{-N}$ in raw water exceeds the Maximum Concentration Limit (MCL), which is below 1.5 mg L^{-1} (Hasan *et al.*, 2009). A high $\text{NH}_4^+\text{-N}$ level in raw water complicates the chlorination process because of the yield of chloramines (Okoniewska *et al.*, 2007). It also causes nervous system damage and deteriorates the taste and odour of water (Markesbery *et al.*, 1984). In addition, $\text{NH}_4^+\text{-N}$ in the water will reduce the reflection of oxygen, eutrophication of surface water and increase toxicity to aquatic life (Tekerlekopoulou and Vayenas, 2007). The Mn^{2+} in drinking water can also affect the human nervous system. Its reaction with chlorine can introduce dirt and corrosion into water distribution

systems (Pacini *et al.*, 2005). Therefore, it is necessary to develop a new water treatment system which focuses on simultaneous NH_4^+ -N and Mn^{2+} removal in order to minimize plant shutdown because of higher NH_4^+ -N and Mn^{2+} content in the water (Hasan *et al.*, 2011b). This would also reduce water shortage and interruption of everyday activities. The NH_4^+ -N and Mn^{2+} were focused in this because these two pollutants always become a main problem in Malaysian drinking water sources.

The Biological Aerated Filter (BAF) is the most suitable additional system in Drinking Water Treatment Plants (DWTP) and is well known in wastewater treatment but not in drinking water treatment (Hasan *et al.*, 2011b, c, 2012, 2013). There is also a test involving combination of conventional care and treatment through successive pre-oxygenation treatments (You and Chen, 2008). Its reactor is flexible and can remove suspended solids, especially in aerobic biological treatment (Su *et al.*, 2007). The BAF is also capable of treating water with high organic load (Mann and Stephenson, 1997). Introducing BAF into conventional DWTP (coagulation, flocculation and filtration) could enhance the performance and functionality of DWTP to produce safe drinking water. The main function of this biofilter is to simultaneously remove NH_4^+ -N and Mn^{2+} from contaminated raw water when it's pollutes at high loading rate which is could not be treated by current conventional drinking water treatment.

It is challenging to simultaneously remove NH_4^+ -N and Mn^{2+} from drinking water using a single treatment system because of the different Oxidation-Reduction Potential (ORP), DO concentration and pH required for oxidation of NH_4^+ -N than that of Mn^{2+} . The NH_4^+ -N may interfere with the operation of Mn^{2+} removal filters because too much oxygen is consumed by nitrification, which results in mouldy, earthy-tasting water (WHO., 2003). When drinking water contains both NH_4^+ -N and Mn^{2+} , biological Mn^{2+} can only be removed after complete nitrification due to the necessary evolution of the redox potential (Frischherz *et al.*, 1985; Vandenabeele *et al.*, 1995; Harris *et al.*, 1996) but it is not possible to remove simultaneously depending on the operating and microorganism involves in the treatment process. The complicated removal of both pollutants in a single treatment is time-consuming and expensive to operate and maintain. Therefore, by controlling the simultaneous removal of NH_4^+ -N and Mn^{2+} through neural network, the system operation of treatment can be automatically stopped. Most of the previous studies only focus on the factors affected simultaneous removal itself but not on the control to predict and stop the treatment once the complete removal of NH_4^+ -N and Mn^{2+} achieved. Moreover, by controlling the DO, ORP and pH, the simultaneous NH_4^+ -N and Mn^{2+} removal may more effective and reduce the cost of the BAF water treatment system compared with offline on/off system. This is because offline on/off system are often time consuming, costly and sticky.

The neural network is based on the idea of neurons in the human brain. It can discover complex formulas and has little to do with simulating intelligence. It can be applied in business, finance, image processing (Srinivasan *et al.*, 2005), control systems (Imtiaz *et al.*, 2013), wastewater treatment (Loh *et al.*, 1995) and many more areas. The system is established in BAFs in order to control aeration. The relevant bending points can be detected in DO, ORP and pH profiles but are clearer in the DO profile. In this study, a neural network automatically controls the aeration supplied to a BAF with a DO profile as its reference when the bending point is detected in the DO profile. The BAF system is monitored in real time so that every piece of data can be recorded without exception. The performance of removal can be improved as aeration into the system can be stopped automatically after detection of bending points, thus saving time and reducing the cost of operation and human supervision. The neural network can also predict the current value from the real-time data for all parameters (DO, ORP, pH, NH_4^+ -N and NO_3^- -N).

To our best knowledge, there is still no study on aeration control based on neural network in BAF system for simultaneous $\text{NH}_4^+\text{-N}$ and Mn^{2+} removal. The main objective of this study is to control aeration based on neural network prediction data that were developed according to real-time data. The aeration control was set to stop when the relevant bending points on the DO pattern detected by the neural network indicated that $\text{NH}_4^+\text{-N}$ and Mn^{2+} had been removed to below the permissible levels.

MATERIALS AND METHODS

Synthetic contaminated water: A Synthetic Contaminated Drinking Water (SCDW) was prepared from tap water. The SCDW consisted of glucose ($\text{C}_6\text{H}_{12}\text{O}_6$: $105 \pm 6 \text{ mg COD L}^{-1}$), ammonium sulphate ($(\text{NH}_4)_2\text{SO}_4$: $10 \pm 0.2 \text{ mg NH}_4^+\text{-N/L}$), manganese chloride ($\text{MnCl}_2 \cdot 4\text{H}_2\text{O}$: $0.35 \text{ mg Mn}^{2+}\text{/L}$), sodium bicarbonate (NaHCO_3 : 100 mg L^{-1}), magnesium chloride ($\text{MgCl}_2 \cdot 6\text{H}_2\text{O}$: 8 mg L^{-1}), iron chloride ($\text{FeCl}_3 \cdot 6\text{H}_2\text{O}$: 0.3 mg L^{-1}), calcium chloride ($\text{CaCl}_2 \cdot 2\text{H}_2\text{O}$: 4.5 mg L^{-1}) and potassium dihydrogen phosphate (KH_2PO_4 : 2.5 mg L^{-1}). All the chemicals used were reagent grade salts (System, Malaysia). The water contamination levels as well as $\text{NH}_4^+\text{-N}$ and Mn^{2+} were simulated, based on the real contaminations in Malaysian rivers (Hasan *et al.*, 2011a). Furthermore, the contamination of $\text{NH}_4^+\text{-N}$ in drinking water sources was also based on a report from the Department of Environment (DOE), Malaysia (DOE., 2014) that in several rivers $\text{NH}_4^+\text{-N}$ contamination was higher than 10 mg L^{-1} .

Set-up and operation of BAF system: The designed BAF system consists of an EX9837 terminal board, signal transmitters, RCCB, MCCB, control panel, rack, analysers of DO, ORP, pH, $\text{NH}_4^+\text{-N}$ and $\text{NO}_3^-\text{-N}$ sensors, compressor, tanks, reactor, pump, air valve, flow meter, Personal Computer (PC), parallel cable and relay. Figure 1 shows the schematic diagram of the BAF system. The BAF column which was made from transparent polyvinyl chloride (PVC) had a height (H) of 150 cm and a diameter (D) of 16 cm with an effective working volume of 15 L. An adjustable stainless steel mesh was located at a height of 120 cm (at sampling port 6: SP6) creating a 20 cm buffer zone to prevent plastic media from being washed out during the backwash process. The BAF column was partially packed with polypropylene media (floating type) with a designed dimension ratio (H/D) of 0.625, density (ρ) of 888 kg m^{-3} and specific surface area (A_s) of $450 \text{ m}^2\text{/m}^3$. The floating media type was used because it had a large surface area that was more suitable for biofilm attachment and enhancement.

An EX9837 terminal board manufactured by TOPSCCC (Taiwan) was used to provide communication between the PC (via serial port) and other peripherals such as pumps, sensors and analysers. Probes for pH (Model PD1R1 GLI, USA), ORP (Model PD1R1 GLI, USA) and DO (Model 5400 GLI, USA) were connected to their respective GLI analysers (Model 33, USA) for respective pH, ORP and DO measurement in the contaminated drinking water. $\text{NH}_4^+\text{-N}$ and $\text{NO}_3^-\text{-N}$ were measured by means of Swansensor $\text{NH}_4^+\text{-N}$ and $\text{NO}_3^-\text{-N}$ Ion Selective Electrodes (ISEs) and analyzed by SWAN meters (FAM: Ammonium, FAM: Nitrate, Switzerland).

The contaminated drinking water inside an influent tank was filled into the BAF reactor with a peristaltic pump (Masterflex, USA) to occupy the BAF column in about 30 min. After the filling period, the software program started the treatment operation and supplied aeration (air on) throughout the BAF column (Fig. 2). It monitored online the values of DO, ORP, pH, $\text{NH}_4^+\text{-N}$ and $\text{NO}_3^-\text{-N}$ from the sensors located inside the column. The software analyzed and controlled the

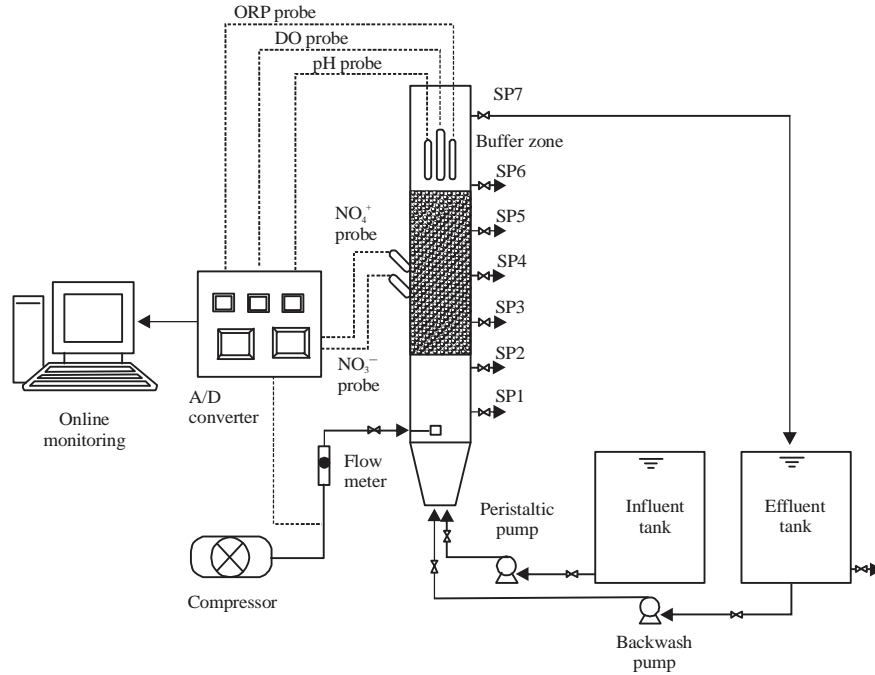


Fig. 1: Schematic of BAF system

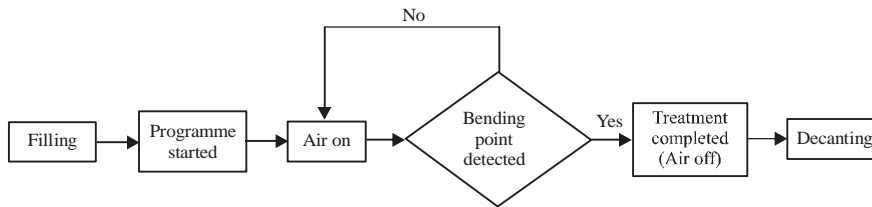


Fig. 2: Control strategy of aeration based on neural network programming

treatment operation by means of a neural network. When the bending point of DO was detected, the program stopped the operation of aeration supply (air off) and consequently shut down the whole operation. If the DO bending point was not detected, the air valve remained open until the reaction was completed.

An air compressor (PUMA XN2040, Taiwan) was connected at the bottom of the BAF to provide aeration with an optimum flow rate of 0.3 mL min⁻¹ as determined from a previous study (Hasan *et al.*, 2011b), to create an aerobic condition throughout the column. Moreover, an air diffuser was used to distribute the aeration through the column to ensure homogenized conditions of air transfer. Backwash was frequently operated every two weeks in a co-current manner to remove the excessive accumulated biomass on the media to prevent the BAF column from clogging and to maintain the biofilm activity inside. The backwash water flow rate was set at 10 L min⁻¹ on average and adjusted as required through the backwash valve and the air flow rate was maintained at 0.3 L min⁻¹. Backwash was performed according to the following procedures: (1) Air scouring for about 5 min at the bottom of the column, (2) Simultaneous air and recycled backwash water for 5 min and finally (3) Air and water flow stopped and column contents allowed to settle for 10 min before withdrawal of the backwash water from the column.

Neural network design: NeuralWork Predict[®] (Version 3.24, USA) software is an advanced modelling and data mining platform for building robust neural networks to analyze data, produce knowledge and reveal complex or unknown relationships in data. A constructive method is used to determine a suitable number of hidden nodes and is referred to as cascade learning (Fahlman and Lebiere, 1990). Real-time data was used to design a model of a neural network controller. Predict[®] selected testing and validation sets of real-time data. Then the selected data was analyzed and transformed. After that, the key variables were selected to construct, train and validate the network model. With more inputs and hidden layers, the neural network design becomes more complicated. In NeuralWork Predict[®], there is a function called FlashCode that can be used to convert the model that has been designed into programming languages such as C++, Visual Basic (VB) and FORTRAN (NeuralWare, 2002).

NeuralWork Predict[®] software created new prediction data of DO, ORP, pH, NH₄⁺-N and NO₃⁻-N for the BAF system based on real-time data. The inputs were DO, ORP, pH, NH₄⁺-N and NO₃⁻-N data and predicted value was the output. Figure 3 shows the neural network architecture of the BAF system for simultaneous NH₄⁺-N and Mn²⁺ removal. NeuralWork Predict[®] selected suitable inputs only for the respective parameters. Each parameter had different suitable inputs.

Software development: In the BAF system, a data acquisition card (EX92026, TOPSCCC, Taiwan) is used as a middle man between software and hardware. The sensors (DO, ORP, pH, NH₄⁺-N and NO₃⁻-N) from the BAF send signals to the data acquisition card and then the software converts those signals into values that represent sensor reading values. The Graphical User Interface (GUI) is very important as it provides control and monitor functions for the BAF system. The data measured by sensors can be monitored and the BAF operation controlled through the GUI. The GUI is generated by Microsoft Visual Basic (version 6, USA) programming language. The GUI of the BAF system can be seen in Fig. 4. The 'Real-Time Meter' shows the actual value of the parameter reading and the 'Neural Network Meter' shows the predicted value. The graphs show the patterns of real-time data that can display 1000 data at a time. All these data can be saved inside the computer for further analysis. The acid, alkaline and air pumps can be controlled by pressing the respective buttons inside the 'Pump Control' box. The pH value can also be set inside the 'Set pH' box. The 'Start/Stop' button is used to start or stop the BAF system operation manually. In this study, only the air pump's on and off buttons were used in order to control the aeration supplied from the 'Pump Control' box.

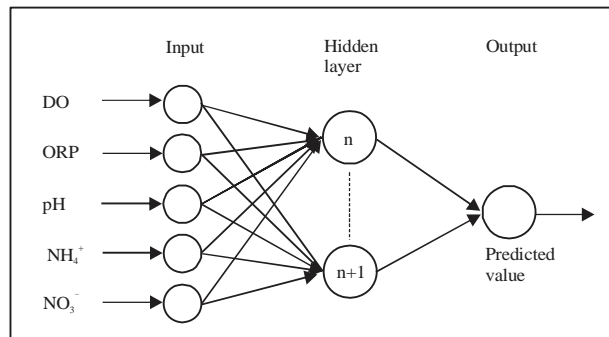


Fig. 3: Neural network architecture

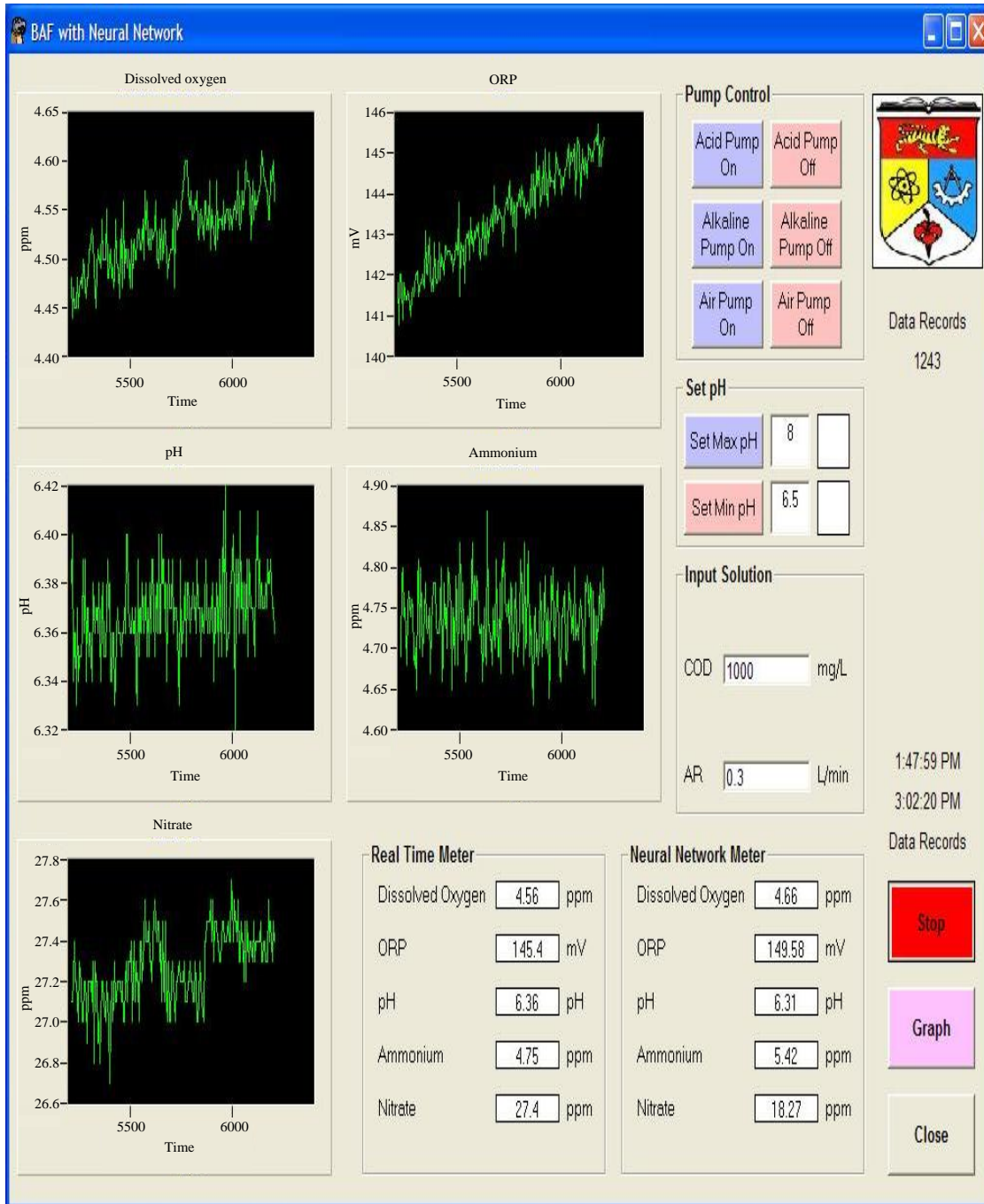


Fig. 4: Graphical user interface of real-time and neural network prediction of biological aerated filter system

Offline measurement

Analytical methods: Sampling was done at sampling point 6 (Fig. 1) and collected in 1 L plastic bottles. A nitrate cellulose membrane filter measuring 0.45 µm (Whatman, USA) was used to filter the excessive Mixed Liquor Suspended Solid (MLSS), according to the standard method. The NH₄⁺-N was analysed through the Nesslerisation method (Method 8038) at an absorbance of

425 nm. Manganese concentration presented as Mn^{2+} was measured with the PAN method (Method 8149) at an absorbance of 560 nm. Nitrate (NO_3^- -N) was analysed through the Cadmium Reduction Method (Method 8039) at an absorbance of 355 nm. All of the parameters were measured with a HACH spectrophotometer DR/2010 (USA).

RESULTS AND DISCUSSION

Neural network prediction: The neural network predicted values of DO, pH, ORP, NH_4^+ -N and NO_3^- -N parameters by creating a prediction model based on real-time data. Then, the program predicted current data by using a neural network algorithm without referring to the real-time data. As can be seen in Fig. 5, the values of predicted data were almost as accurate as the real-time data with overall errors below 2.5% for DO, 0.8% for pH, 1.5% for ORP, 3% for NH_4^+ -N and 3% for

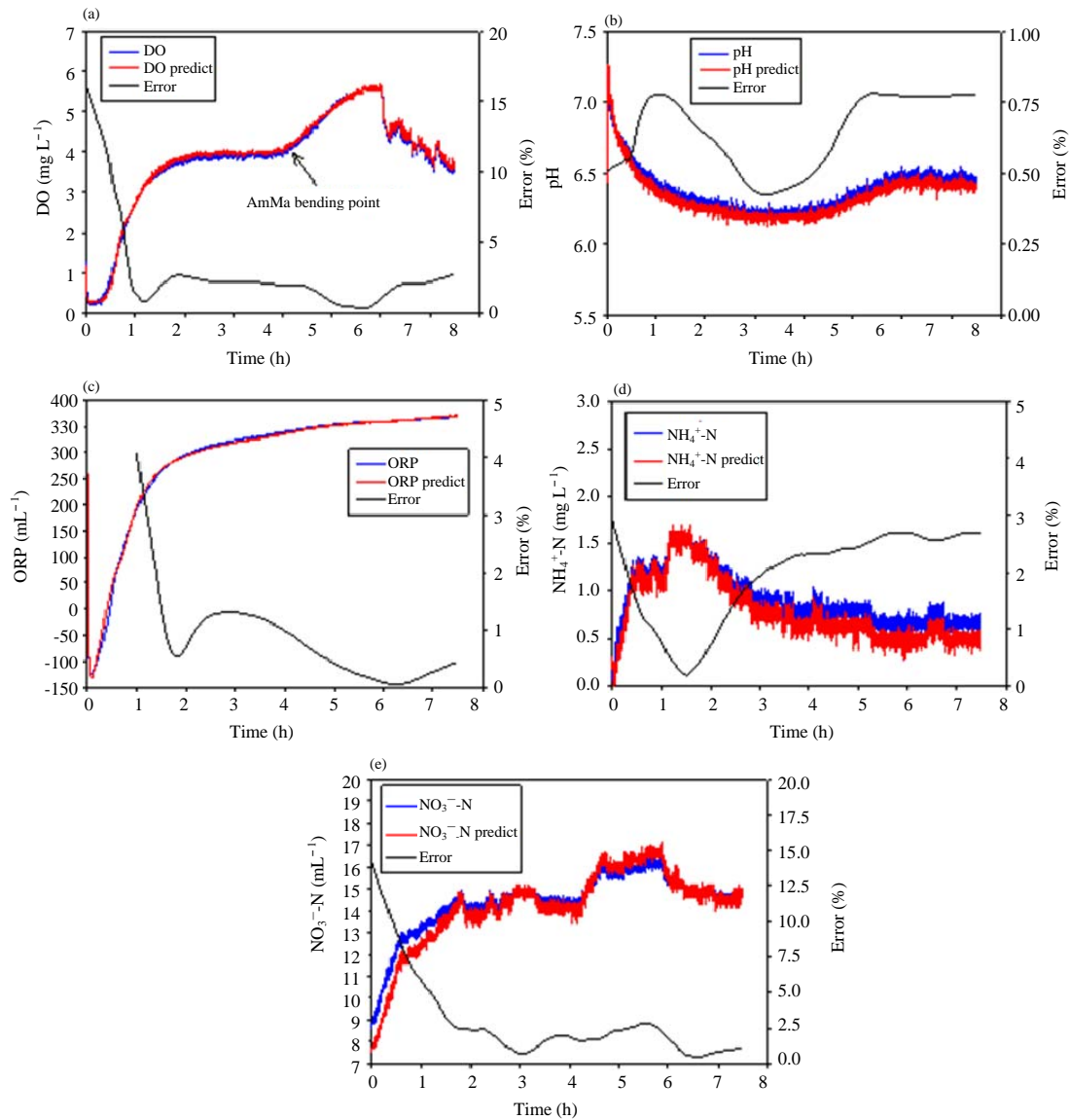


Fig. 5(a-e): Profiles of real-time and neural network prediction values for (a) DO, (b) pH, (c) ORP, (d) NH_4^+ -N and (e) NO_3^- -N

NO_3^- -N. This showed that neural network prediction was a viable alternative for developing, measuring and controlling the parameters of DO, pH and ORP in a BAF system for the simultaneous removal of NH_4^+ -N and Mn^{2+} from drinking water.

Neural network control of BAF operation: The relevant bending points in DO, ORP and pH need to be identified for automatic control of the BAF operation by the neural network. In this study, the DO pattern was adopted as the main control parameter because its bending point could be seen more clearly. Aeration in the reactor was essential to supply sufficient DO for biofilm in order to treat the SCDW by simultaneous oxidization of NH_4^+ -N and Mn^{2+} . After the NH_4^+ -N and Mn^{2+} had been removed to below MCLs, the aeration supplied to the reactor was stopped, consequently reducing energy consumption and wastage.

The treatment process was complete when the Am-Mn bending point appeared in DO (Fig. 5a). Figure 5a shows that the DO value increased rapidly after the aeration was supplied (treatment process started). Then it became more stable because during this period (2-4 h) the biofilm consumed a lot of DO for simultaneous oxidization of NH_4^+ -N and Mn^{2+} and later created an Am-Mn bending point after 4 h. The bending point was detected by the neural network program and a signal was sent to the air valve to stop supplying aeration to the BAF. Immediately after that, the DO value dropped rapidly as there was no aeration supplied to the BAF. The software detected the Am-Mn bending point by analyzing the DO aeration slope as shown in Fig. 6. It started analyzing the DO aeration slope immediately after the 4 h mark. In the first 4 h, the treatment was still in process and the concentrations of NH_4^+ -N and Mn^{2+} were detected below the MCL. The slope increased after the first 4 h and the software only detected when it decreased (after 5 h). The software sent a signal to the air valve to stop aeration as the treatment process was completed. Figure 6 also shows a graph of the air valve opening. The air valve supplied aeration (On: 1) for about 5.5 h. Nearer to 6 h, the air valve started to bounce as it received a signal from the software that the process of simultaneous NH_4^+ -N and Mn^{2+} removal was almost completed. The air valve stopped the aeration (Off: 0) after 6 h.

By controlling DO using the neural network, it can accurately recognize the actual completion time of simultaneous NH_4^+ -N and Mn^{2+} removal through the bending point as detected on the DO profile. According to Yu *et al.* (2014), the removal efficiencies of Cr(VI) was well correlated with pH,

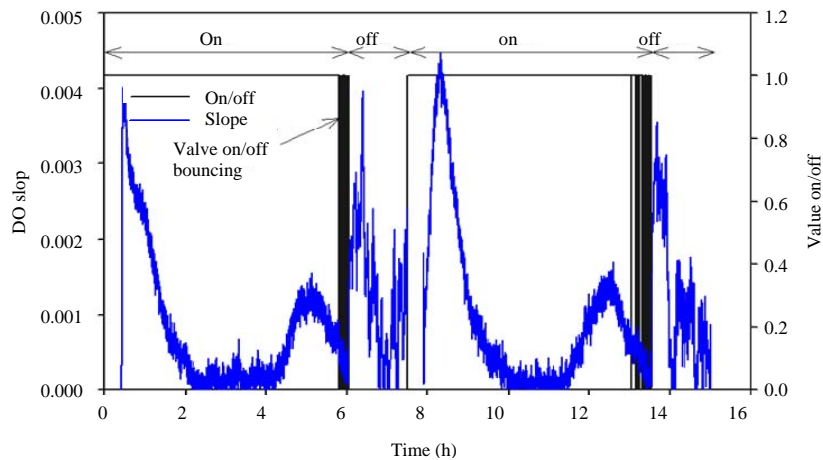


Fig. 6: Slope of DO and indication of on/off air valve

ORP and DO values using back propagation neural network model. Moreover, by using neural network to control synthetic wastewater treatment through ORP monitoring, Yu *et al.* (2010) found that the neural network can predict precisely the colour and Chemical Oxygen Demand (COD) removal efficiencies.

In this study, without the recognition points detected by neural network, the aeration will not be stopped. Once the bending point was detected, the neural network program sent a signal to software to stop the aeration supplement. Through this technique, the power consumption for aeration supply can be automatically stopped and consequently reduced the cost compared to the conventional on/off aeration control. In conventional control of DO on/off more costly and time consuming are required in measuring the actual completion time of $\text{NH}_4^+\text{-N}$ and Mn^{2+} . Surmacz-Gorska *et al.* (1996) stated in their study that by using online monitoring in removing ammonia using activated sludge treatment, the aeration energy cost can be saved and more constant effluent quality can be achieved.

Verification through offline monitoring: In order to treat the contaminated drinking water from $\text{NH}_4^+\text{-N}$ and Mn^{2+} , the effluent concentrations of $\text{NH}_4^+\text{-N}$ and Mn^{2+} had to stay within the regulated limits which were below 1.5 and 0.1 mg L^{-1} , respectively. The Am-Mn bending point in the DO pattern implied that the amount of $\text{NH}_4^+\text{-N}$ and Mn^{2+} in the contaminated drinking water had decreased to minimum and was almost eliminated. This was confirmed by offline monitoring of $\text{NH}_4^+\text{-N}$ and Mn^{2+} concentrations. As shown in Fig. 7, the $\text{NH}_4^+\text{-N}$ and Mn^{2+} values decreased as longer the retention time. The effluent quality reached the MCL after 4 h with lower concentrations of 0.41 mg L^{-1} for $\text{NH}_4^+\text{-N}$ and 0.01 mg L^{-1} for Mn^{2+} and afterward simultaneous removal occurred for 7.5 h at a very slow removal rate. Thus, the Am-Mn bending points in the DO pattern (Fig. 5a) proved that the simultaneous removal of $\text{NH}_4^+\text{-N}$ and Mn^{2+} had been fully achieved. By using two stage Sequencing Batch Reactor (SBR) to treat animal wastewater, Ra *et al.* (1998) found that the DO levels immediately increased once ammonia-N completely removed, which also lowered the Oxygen Uptake Rate (OUR) by the bacteria.

Furthermore, comparison between offline and real-time measurement for $\text{NH}_4^+\text{-N}$ and $\text{NO}_3^-\text{-N}$ showed similar patterns but a huge difference in measurement values. The $\text{NH}_4^+\text{-N}$ concentrations showed a decreasing trend, whereas the pattern of $\text{NO}_3^-\text{-N}$ production increased. As shown in Fig. 5d, the reading of $\text{NH}_4^+\text{-N}$ during the 1st h of reaction increased but its trend decreased until

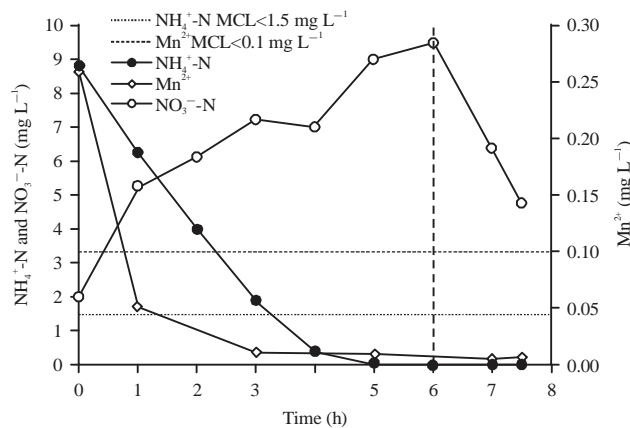


Fig. 7: Offline monitoring of simultaneous $\text{NH}_4^+\text{-N}$ and Mn^{2+} removal

7.5 h had elapsed, as also represented by offline measurement (Fig. 7). This was because the NH_4^+ -N probe used for the real-time reading required a period of adaptation for stabilization. As the Am-Mn bending point was achieved after 4 h, NO_3^- -N trends for both measurement methods (real-time and offline) slightly declined because of the DO pattern that started to shift up to a new plateau. The trend of NO_3^- -N decreased until the end of the treatment cycles when the aeration valve was automatically shut off by the neural network. Thus, even though real-time monitoring of NH_4^+ -N and NO_3^- -N gave inaccurate readings, it could be useful as an alternative because its pattern along the treatment cycles was similar to that of offline monitoring.

CONCLUSION

From the results obtained it is clear that NH_4^+ -N and Mn^{2+} contents in contaminated drinking water can be simultaneously removed by means of a BAF system. The Am-Mn bending point in the DO profile showed that the contaminated drinking water had been successfully treated to below MCLs. The neural network successfully predicted the values of DO, ORP, pH, NH_4^+ -N and NO_3^- -N. The results also indicated that the drinking water treatment process can be controlled by use of a neural network. The program analysed the Am-Mn bending point of the DO pattern by using the DO slope as a reference point. The aeration in the BAF stopped after the Am-Mn bending point detected the complete and simultaneous removal of NH_4^+ -N and Mn^{2+} . Thus, it could save on the energy and operating costs of the BAF system.

ACKNOWLEDGMENTS

This study was financially supported by the Ministry of Science, Technology and Innovation (MOSTI), Malaysia through grant number 02-01-02-SF0367 and also supported by Universiti Kebangsaan Malaysia funding for young researchers through grant number GGPM-2013-075.

REFERENCES

- DOE., 2014. Yearly annual report. <http://www.doe.gov.my/en/annualreport;2003-2009>.
- Fahlman, S.E. and C. Lebiere, 1990. The Cascade-Correlation Learning Architecture. In: *Advances in Neural Information Systems II*, Touretzky, D.S. (Ed.). Morgan Kaufmann Publishers, Morgan, pp: 524-532.
- Frischherz, H., F. Zibuschka, H. Jung and W. Zerobin, 1985. Biological elimination of iron and manganese. *Water Supply*, 3: 125-136.
- Harris, S.L., T. Stephenson and P. Pearce, 1996. Aeration investigation of biological aerated filters using off-gas analysis. *Water Sci. Technol.*, 34: 307-314.
- Hasan, H.A., S.R.S. Abdullah, S. Kamaruddin and N.T. Kofli, 2009. A review on the design criteria of biological aerated filter for COD, ammonia and manganese removal in drinking water treatment. *J. Inst. Eng. Malaysia*, 70: 25-33.
- Hasan, H.A., S.R.S. Abdullah, S.K. Kamarudin and N.T. Kofli, 2011a. Effect of Organic Carbon Loading (OCL) on simultaneous NH_4^+ -N and Mn^{2+} removal in drinking water using a BAF system. *Environ. Eng. Manage. J.*, 10: 1733-1742.
- Hasan, H.A., S.R.S. Abdullah, S.K. Kamarudin and N.T. Kofli, 2011b. Problems of ammonia and manganese in Malaysian drinking water treatments. *World Applied Sci. J.*, 10: 1890-1896.
- Hasan, H.A., S.R.S. Abdullah, S.K. Kamarudin and N.T. Kofli, 2011c. Response surface methodology for optimization of simultaneous COD, NH_4^+ -N and Mn^{2+} removal from drinking water by biological aerated filter. *Desalination*, 275: 50-61.

- Hasan, H.A., S.R.S. Abdullah, N.T. Kofli and S.K. Kamarudin, 2012. Effective microbes for simultaneous bio-oxidation of ammonia and manganese in biological aerated filter system. *Bioresour. Technol.*, 124: 355-363.
- Hasan, H.A., S.R.S. Abdullah, S.K. Kamarudin and N.T. Kofli, 2013. Simultaneous ammonia and manganese removal from drinking water by using BAF system: Effect of different aeration rate. *Sep. Purif. Technol.*, 118: 547-556.
- Imtiaz, U., A. Assadzadeh, S.S. Jamuar and J.N. Sahu, 2013. Bioreactor temperature profile controller using Inverse Neural Network (INN) for production of ethanol. *J. Process Control.*, 2: 731-742.
- Loh, A.P., K.O. Looi and K.F. Fong, 1995. Neural network modelling and control strategies for a pH process. *J. Process Control*, 5: 355-362.
- Mann, A.T. and T. Stephenson, 1997. Modelling biological aerated filters for wastewater treatment. *Water Res.*, 31: 2443-2448.
- Markesbery, W.R., W.D. Ehmann, M. Alauddin and T.I.M. Hossain, 1984. Brain trace element concentrations in aging. *Neurobiol. Aging*, 5: 19-28.
- NeuralWare, 2002. *NeuralWorks Predict User Guide*. NeuralWare, Inc., Carnegie, PA.
- Okoniewska, E., J. Lach, M. Kacprzak and E. Neczaj, 2007. The removal of manganese, iron and ammonium nitrogen on impregnated activated carbon. *Desalination*, 206: 251-258.
- Pacini, V.A., A.M. Ingallinella and G. Sanguinetti, 2005. Removal of iron and manganese using biological roughing up flow filtration. *Water Res.*, 39: 4463-4475.
- Ra, C.S., K.V. Lo and D.S. Mavinic, 1998. Real-time control of two-stage sequencing batch reactor system for the treatment of animal wastewater. *Environ. Technol.*, 19: 343-356.
- Srinivasan, R., C. Wang, W.K. Ho and K.W. Lim, 2005. Neural network systems for multi-dimensional temporal pattern classification. *Comput. Chem. Eng.*, 29: 965-981.
- Su, D., J. Wang, K. Liu and D. Zhou, 2007. Kinetic performance of oil-field produced water treatment by biological aerated filter. *Chin. J. Chem. Eng.*, 15: 591-594.
- Surmacz-Gorska, J., K. Gernaey, C. Demuyne, P. Vanrolleghem and W. Verstraete, 1996. Nitrification monitoring in activated sludge by oxygen uptake rate (OUR) measurements. *Water Res.*, 30: 1228-1236.
- Tekerlekopoulou, A.G. and D.V. Vayenas, 2007. Ammonia, iron and manganese removal from potable water using trickling filters. *Desalination*, 210: 225-235.
- Vandenabeele, J., M.V. Woestyne, F. Houwen, R. Germonpre, D. Vandensande and W. Verstraete, 1995. Role of autotrophic nitrifiers in biological manganese removal from groundwater containing manganese and ammonium. *Microbiol. Ecol.*, 29: 83-98.
- WHO., 2003. *Ammonia in drinking-water. Background document for preparation of WHO Guidelines for drinking-water quality*. Geneva, World Health Organization (WHO/SDE/WSH/03.04/1).
- You, S.J. and W.Y. Chen, 2008. Ammonia oxidizing bacteria in a nitrite-accumulating membrane bioreactor. *Int. Biodeter. Biodegrad.*, 62: 244-249.
- Yu, R.F., H.W. Chen, K.Y. Liu, W.P. Cheng and P.H. Hsieh, 2010. Control of the Fenton process for textile wastewater treatment using artificial neural networks. *J. Chem. Technol. Biotechnol.*, 85: 267-278.
- Yu, R.F., F.H. Chi, W.P. Cheng and J.C. Chang, 2014. Application of pH, ORP and DO monitoring to evaluate chromium(VI) removal from wastewater by the nanoscale Zero-Valent Iron (nZVI) process. *Chem. Eng. J.*, 255: 568-576.