Bull. Mar. Sci & Tech 12(1):47-54, 2003
Research Institute of Marine Science and Technology
Korea Maritime University

Neural network modeling for nutrient dynamics in a recycling piggery slurry treatment system

Jung-Hye Choi[1], Jun-Il Sohn[2], Minho Lee[3], Sung-Woo Shin[1] and Sung-Cheol Koh[1,*]
[1]*Division of Civil and Environmental Systems Engineering, Korea Maritime University, 1 Dongsam-dong, Youngdo-Gu, Busan 606-791, Republic of Korea*
[2]*Department of Sensor Engineering, Kyungpook National University, Daegu 702-701, Republic of Korea*
[3]*School of Electronic and Electrical Engineering, Kyungpook National University, Daegu 702-701, Republic of Korea*
**Author for correspondence: Tel.: +82-51-4104418, Fax: +82-51-4104415, E-mail: skoh@hanara.kmaritime.ac.kr*

Received 13 August 2001; accepted 7 September 2002

Keywords: *Alcaligenes faecalis*, lactic acid bacteria (LAB), neural network, piggery slurry, principal component analysis (PCA)

Summary

A recycling reactor system operated under sequential anoxic and oxic conditions was evaluated, in which the nutrients of piggery slurry were anaerobically and aerobically treated and then a portion of the effluent was recycled to the pigsty. The most dominant aerobic heterotrophs from the reactor were *Alcaligenes faecalis* (TSA-3), *Brevundimonas diminuta* (TSA-1) and *Abiotrophia defectiva* (TSA-2) in decreasing order, whereas lactic acid bacteria, LAB (MRS-1, etc.) were most dominantly observed in the anoxic tank. Here we have tried to model the nutrient removal process for each tank in the system based on population densities of heterotrophic and LAB. Principal component analysis (PCA) was first applied to delineate a relationship between input (microbial densities and treatment parameters such as population densities of heterotrophic and LAB, suspended solids (SS), COD, NH_4^+—N, *ortho*-phosphorus, and total phosphorus) and output. Multi-layer neural networks using an error back-propagation learning algorithm were then employed to model the nutrient removal process for each tank. PCA filtration of microbial densities as input data was able to enhance generalization performance of the neural network, and this has led to a better prediction of the measured data. Neural networks independently trained for each treatment tank and the combined analysis of the subsequent tank data allowed a successful prediction of the treatment system for at least 2 days.

Introduction

Piggery slurry may cause a serious degradation of water quality such as eutrophication and spread of pathogens in water bodies (i.e., lakes, rivers and groundwater as water supply sources) (Shin *et al.* 1990). The daily volume of livestock wastewater in Korea has reached 197,000 m^3, half of the volume being generated from dairy farms that are not under legal pollution control. The amount of wastewater is relatively small compared with total wastewater including industrial and domestic wastewater (7% of the total), but contributes significantly to the pollution of the receiving waters because of its high organic nutrient concentration (>BOD 20,000 mg l^{-1}) (Shin *et al.*) 1990 While an activated sludge system has been proved to be effective in the treatment of piggery slurry in large farms (more than 1000 heads), the system may not be appropriate in small- or middle-scale farms (less than 1000 heads) in the aspect of its operation cost.

Recently a new reactor system for swine wastewater treatment operated under sequential oxic and anoxic conditions has been developed, in which piggery slurry is fermentatively and aerobically treated and then a portion of the effluent recycled to the pigsty (Choi *et al.* 1999). In practice, this system seemed to significantly remove offensive smells (at both pigsty and treatment plant) and BOD, and turned out to be cost-effective for relatively small-scale farms.

One of the well-known models applied for wastewater treatment system is the activated sludge model no. 1 (ASM 1) introduced by International Association for Water Quality (IAWQ) (Henze *et al.* 1987). Application of this structured model to a field wastewater treatment system, however, may have some limitations because many microbial reactions coupled with environmental complexity are non-linear and time-sensitive, and are often hard-to-measure using a linear analysis system (Lee & Park 1999, 2000).

On the other hand, neural network models that imitate the functions of our human brain have been successfully used to resolve many engineering problems such as complex pattern recognition and control of highly non-linear dynamic systems (Barto *et al.* 1983; Morgan & Scofield 1991; Lee *et al.* 1992; Weigend & Gershenfeld 1994). These models have the characteristics of massive parallelism, many degrees of freedom, and adaptive learning. It became recently known that multi-layer neural networks could approximate a function in L^p within an arbitrary accuracy (Hornik 1991), and generalize a new dataset that was not used in the learning process (Baum & Hausser 1989). Progress has also been made in application of neural networks to control biological and chemical engineering processes including biological wastewater treatment (Cote *et al.* 1995; Zhao *et al.* 1997; Lee & Park 1999). There has been, however, no report dealing with neural network modeling for nutrient removal in a recycling swine wastewater treatment process.

This study was performed to elucidate the mechanism of the recycling piggery slurry treatment process using variables such as microbial population density and treatment effects based upon suspended solids (SS), total nitrogen (T-N), ammonia nitrogen (NH_4^+—N), total phosphorus (T-P), *ortho*-phosphorus (*o*-P) and chemical oxygen demand (COD) as input or output variables. These variables were used to establish a non-linear model emulator using multi-level neural networks that could eventually allow a real time monitoring and prediction of the treatment system, and the system optimization.

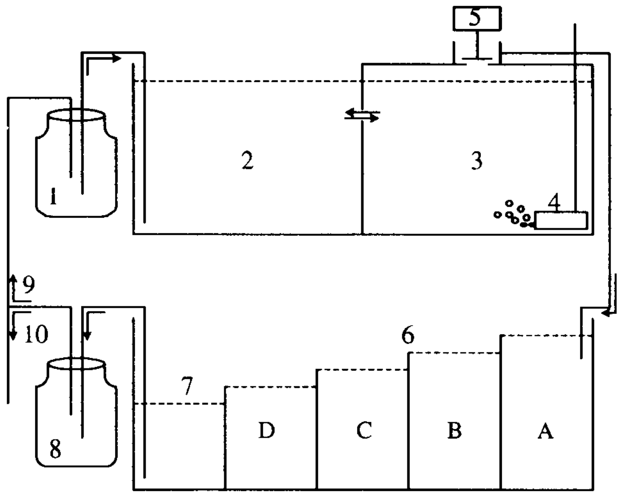

Figure 1. Schematic diagram of the recycling treatment system for piggery slurry. (1) Influent tank; (2) fermentation tank; (3) aeration tank; (4) blower; (5) antifoaming device; (6) sedimentation tanks (A–D); (7) reservoir; (8) storage tank; (9) recycling flow; (10) for land application as a fertilizer (Choi *et al.* 2000).

Materials and methods

Description of treatment system

A schematic diagram of the bench scale recycling treatment system is shown in Figure 1. Influent composed of piggery slurry and recycled effluent was collected in tank 1, and the influent then flows into the fermentation tank (tank 2; working volume 13.2 l). A portion of the effluent was used as washing water for pigsty in the full scale treatment system. There is a hole between tank 2 and aeration tank (tank 3; working volume 13.2 l) so that the fermented wastewater can be transported into tank 3 where aerobic treatment occurs under aeration conditions (7.8 v/v/m). Hydraulic retention times (HRT) of the fermentation and the aeration tank were 3.6 days. The treated wastewater then goes through sedimentation in tanks 6 and 7, and finally is stored in tank 8. The volumes of the sedimentation tanks A, B, C and D were 1.061, 0.874, 0.686 and 0.500 l, and the HRT for the corresponding sedimentation tanks were 6.80, 5.60, 4.40 and 3.21 h, respectively. The bench scale treatment system was operated for 47 days.

The fresh piggery slurry used in this study was sampled from a mixing and storage tank at Kimhae Piggery Slurry Treatment Plant (Kimhae, Kyungnam, Korea) and had the following parameter values COD (ca. 4000 mg l^{-1}), BOD (ca. 7000 mg l^{-1}), T-N (ca. 2100 mg l^{-1}), and T-P (ca. 172 mg l^{-1}). The influent consisted of fresh piggery slurry (33%, v/v), recycled effluent (57%) and tap water (10%), and each batch of the influent was supplied every 4 days (Choi *et al.* 2000). The average loading rates of the parameters such as COD, T-P, *o*-P, NH_4^+—N and SS in the influent were 3341, 45.24, 43, 1431 and 0.54 mg l^{-1}. Flow rate of the influent was 2.6 ml min^{-1} and the pumping was performed using a peristaltic pump (Model No. AP-60101, Won Corp., Seoul, Korea) with a pump head (Model No. 7518-10, Cole–Palmer Instrument Co., Vernon Hills, IL, USA) and silicone peroxide tubing (Model No. EL-96400-14, Cole–Palmer Instrument Co., Vernon Hills, IL, USA). The effluent was also pumped out from the reservoir (tank 7) using a peristaltic pump system (Model No. 7553-75, Cole–Palmer Instrument Co., Vernon Hills, IL, USA). Glucose was added to the formulated influent to make a C/N ratio of 100:15 (Liao *et al.* 1993) and a proprietary microbial agent (YC2000, Yoonchang Agricultural Management, Inc., Cheju) was also added up to 0.1% (w/v). The microbial agent was added as a fee additive for pigs and as a seeding source for the aeration tank as in the full scale treatment system. We assumed that the microbial populations from the agent were present in the piggery slurry and added the agent to the influent (0.1%, w/v). The agent was also added to the aeration tank of the treatment system (0.1%, w/v), simulating the full scale treatment system. The microbial agent was supposed to contain microbial communities such as *Bacillus* sp., lactic acid bacteria (LAB) and yeast according to the manufacturer's product information.

Enumeration of microorganisms from the treatment system

The bacterial community in the system was analysed based on their isolation, identification and determining the colony forming unit (population density) of dominant populations on a solid medium. Heterotrophic bacteria potentially involved in the piggery slurry treatment within the system were isolated using the appropriate media (Krieg & Gerhardt 1994). To enumerate LAB, de Man–Rogosa–Sharpe (MRS) medium was used. LAB were grown at least 2 weeks before identification and counting were performed. Other heterotrophs were grown on TSA (Trypticase Soy Agar, Difco) for at least 1 week, and then identified and counted.

Analysis of piggery slurry samples from the treatment system

Treatment parameters, such as SS, T-N, NH_4^+—N, T-P, *o*-P and COD, were measured for piggery slurry samples taken daily following Standard Methods for the Examination of Water and Wastewater (American Public Health Association 1992): COD by closed reflux, titrimetric method, T-P and *o*-P by the ascorbic acid method, SS by total SS cride method, and NH_4^+—N by the indophenol method.

Neural network modeling of the treatment system

For an optimization of piggery slurry treatment, it is critical to understand the physiological activities of microorganisms and their relationships, but may not be easy to identify the complex relationships by the conventional linear analytical methods. We therefore decided to use a multi-layer neural network with an error back-propagation algorithm to model the complex relationships in the recycling system as described previously by Choi *et al.* (2000). The developed model using the neural network can be used as an emulator that estimates the treatment system performance depending upon microbial densities without performing an experiment. We can derive an optimal treatment condition based on a simulation using the emulator.

The rationale for modeling of the recycling system is based upon a cause and effect relationships in the sequential tanks. Population densities of dominant heterotrophic microorganisms MRS-1, TSA-1, TSA-2 and TSA-3 isolated in this study were employed as independent parameters because they could grow fast and significantly affect the piggery slurry treatment efficiency. Here ammonium oxidizers were not considered, despite their importance in the swine waste treatment system, because of their slow growth and difficulty in identification. COD, total-P, *o*-P, SS and NH_4^+—N were considered as nutrient removal parameters. Thus, we built a multi-layer neural network in which the input nodes consisted of four independent parameters in the current tank and five treatment parameters from the preceding tank, and the output nodes generated the five treatment parameters in the current tank.

The design and execution of the neural networks were performed following the previous method of Choi *et al.* (2000). Because of the difficulty of modeling the overall characteristics of all tanks by a single neural network due to the complex microbial interactions in the sequential tanks of the treatment system, we employed a neural network modeling of each tank, and then the overall modeling of the whole treatment system was carried out by the connection of each neural network. Figure 2 shows a modeling protocol used for the recycling system. Here principal component analysis (PCA) was employed as a preprocessor of the neural network. Input of the neural network was reduced to three principal values from nine independent variables. The output values of the neural network were COD, T-P, *o*-P, SS and NH_4^+—N in the current tank as described before (Choi *et al.* 2000).

For a successful modeling, the connectivities within neural networks in the current tank were adjusted so that a best prediction of the measured values would be obtained at the next treatment step using SS, NH_4^+—N, T-P, *o*-P and COD as input variables (Figure 3).

Ammonium uptake and utilization test

The ability of the isolated heterotrophs to uptake ammonium (NH_4^+) was measured to analyze the ammonium removal mechanism in the treatment system. The dominant organisms (TSA-1, TSA-2 and TSA-3)

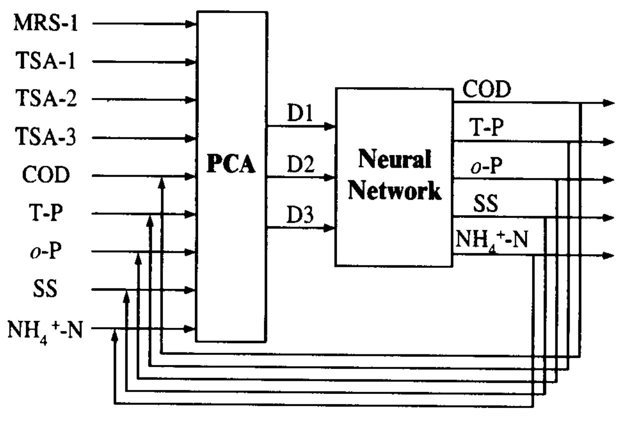

Figure 2. A schematic diagram describing training strategy for the neural networks in this study. MRS-1, TSA-1, TSA-2 and TSA-3 denote each population density of the bacterial strains. COD, T-P, *o*-P, SS and NH_4^+—N are parameters for the wastewater treatment. PCA, D1, D2 and D3 denote principal component analysis and dimensions obtained after the analysis, respectively (Choi *et al.* 2000).

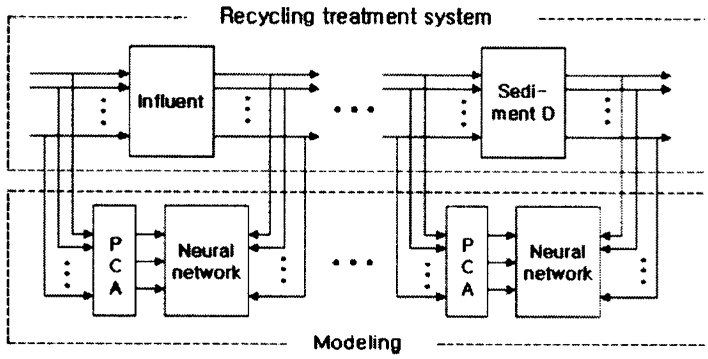

Figure 3. Modeling of the recycling treatment system using series of neural networks.

were grown in the mineral salts medium (Koh *et al.* 1993) containing glucose (0.4 or 3.2% w/v) as a sole carbon source. Unless the organisms were grown on the medium, they were grown in citrate mineral salts medium (Otte *et al.* 1996). The nitrogen source for these media was $(NH_4)_2SO_4$. The inoculated media were incubated at 26 °C and under rotary shaking (190 rev min^{-1}), and the growth was measured spectrophotometrically (525 nm). The ammonium concentrations before inoculation and at stationary phase were measured and the ammonium removal efficiency was calculated.

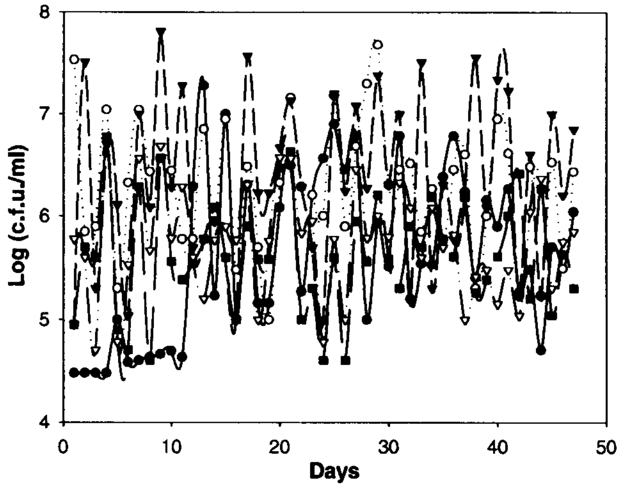

Figure 4. Population dynamics of a heterotrophic bacterium (*Brevundimonas diminuta* TSA-1) in the recycling treatment system ((●) Influent tank; (○) fermentation tank; (▼) aeration tank; (▽) sedimentation tank A; (■) sedimentation tank D).

Results and discussion

Analysis of microbial population dynamics and its relation to piggery slurry treatment

The most dominant heterotrophic bacteria in the treatment system were four aerobic bacteria and three LAB. The identified organisms were TSA-1 (*Brevundimonas diminuta*), TSA-2 (*Abiotrophia defectiva*), TSA-3 (*Alcaligenes faecalis*) and MRS-3 (*Streptococcus* sp.) (Choi *et al.* 2000). The putative *Bacillus* sp. and yeast from the microbial agent were not observed here probably because of their inability to compete with the indigenous microbial populations in the system.

The most dominant aerobe was *Alcaligenes faecalis* TSA-3. The most dominant species of LAB was strain MRS-1. Population dynamics of the representative aerobic bacterium *Alcaligenes faecalis* TSA-3 during the 47-day running period was shown for each tank (Choi *et al.* 2000). This strain was observed in both influent and fermentation tanks, so that it appeared to survive and grow under low oxygen tension and anoxic conditions. A known species of *Alcaligenes faecalis* was able to oxidize ammonia under aerobic conditions and denitrify nitrate ions via NO and N_2O gases under anoxic conditions (Papen *et al.* 1989; Anderson *et al.* 1993). Another strain of the same species was found to accumulate NO_2^- during exponential growth (Otte *et al.* 1996). The next most dominant groups of heterotrophs were TSA-1 (*Brevundimonas diminuta*) (Figure 4) and TSA-2 (*Abiotrophia defectiva*). The population of the strain TSA-1 was dominant in the aeration tank than in the fermentation as shown in Figure 4.

The ammonium removal efficiency reached 41% as a maximum. The reason for this rather low efficiency was not clear but an unbalanced (presumably, lower) C/N ratio would be one of the causes. Here, however, the offensive ammonium smells were significantly reduced in the effluent.

Nitrogen removal through nitrification by ammonium oxidizers and other nitrifiers is also likely since the ammonium oxidizers were observed in the full scale system (unpublished data of the corresponding author). Anaerobic denitrification would be possible in the fermentation tank, although we did not try to measure nitrogen gas evolution. Actually in the fermentation tank, we were able to observe evolution of unidentified gases that might include CO_2, N_2, and organic gases.

A further description of other microbial population dynamics and potential activities was made in the previous report (Choi *et al.* 2000): the overall COD removal efficiency was 54%; the *ortho-* or total phosphorus removal effect was at least 40%; the removal effect of SS was 63%. It was assumed that the phosphorus removal resulted from an uptake of phosphorus by cells under aerobic conditions and a subsequent sedimentation of the cells. Surplus phosphorus to be uptaken may be transformed to poly-phosphate as a storage material within the cells (Hiraishi *et al.* 1998). A discharge of phosphorus is known to occur under anaerobic conditions (Bond *et al.* 1999).

Filtration of the input data by PCA

The input and output dimensions of the neural networks in this study were 9 and 5, respectively as described previously by Choi *et al.* (2000). The nine input dimensions include four microbial population densities and five treatment parameters as shown in Figure 2. The nine input dimensions were independent parameters because they were considered as cause parameters for the treatment system. The five treatment parameters were picked as dependent parameters because they were affected by the preceding input parameters. These five dependent parameters were frequently used as monitoring parameters for the wastewater treatment in general. Training data measured for 47 days were not enough to figure out the complex correlation between the input and the output in each tank, and also it was rather hard to expect a generalization. Moreover, there were some noises in the data due to a measuring error or unstable biological process. In order to reduce the input and output dimensions, and to remove the noisy data, we first used the PCA method to analyse the training data. PCA projects high dimensional data onto low dimensional coordinates that consist of principal component axes.

In this study, we used three axes as orthogonal coordinates. These axes were obtained by PCA, removing the data with one-to-many mapping that could give different output from the same inputs.

Modeling of treatment system by neural networks

Among 47 trained data to learn the neural network, we reserved datasets numbers 6, 11, 16, 21, 31, 36, 41, 46 and 47 for the test phase. These were randomly selected and used as test data to evaluate the generalization performance of the neural network. Except the test data, training data were used to train the weights of the neural network. The neural network had one hidden layer with 30 nodes that were determined by an *ad hoc* method and non-linear function of hidden and output layers. The weight values were adjusted by an error back-propagation algorithm.

The learning curves showed decreasing errors depending upon the iteration during the training phase (Figure 5). Here all of the output parameters were successfully trained with the optimal number of hidden nodes determined by trial and error. We used the pattern type error back-propagation learning algorithm

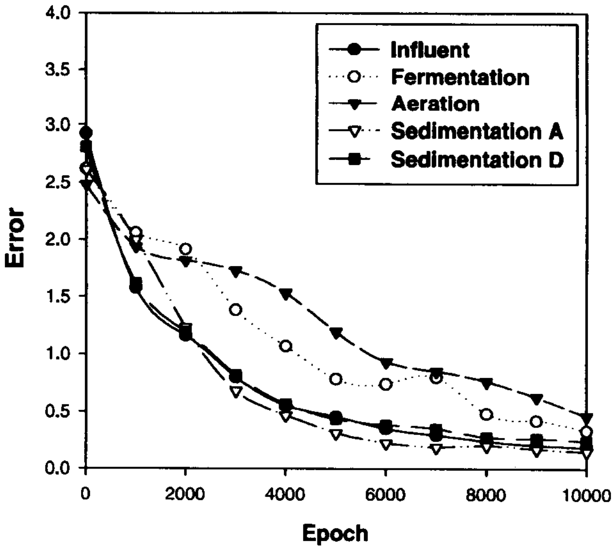

Figure 5. Learning curves of each neural network in the training phase. Note that the errors decrease as the number of epoch increases.

(Simon 1999). The weight values of the neural network in the pattern type learning method were updated for each training pattern, and all of the data were repeatedly used to reduce the epoch error. The epoch error was the average of each pattern error. In order to increase the generalization performance, we considered the cross-validation process that used one-half of the data for the training and the other half for cross-validation (Weigend & Gershenfeld 1994).

Through computational experiments we could establish that the learned neural networks successfully imitated each tank of the treatment system and well approximated the target values of the input pattern. Figure 6 (A–D) showed the prediction results of COD, NH_4^+—N, *o*-P and SS values using the neural network without or with PCA, respectively. The numbers (1–5) on the *X*-axis represent the influent tank, fermentation tank, aeration tank, sedimentation tank A and sedimentation tank D of day 46, respectively while the numbers(6–10) represented the five equivalent tanks of day 47 in order. Although both the recycled water and the new piggery slurry added would adversely affect the prediction performance in various tanks including influent tanks, in particular, the prediction results generally agreed with the measured data except the outlier of SS (0.88) at the influent tank of day 47. The outlier value was not plotted in Figure 6(D). Our treatment system is recycling, and thus the treated wastewater is recycled into the influent tank from sedimentation tank D. Moreover, a portion of the untreated piggery slurry also entered the influent tank. In further research, we need to examine the effects of the recycled water quantity and the amount of added piggery slurry as additional inputs of the neural network.

In order to enhance efficiency of PCA employment, we compared the mean square errors of the predicted

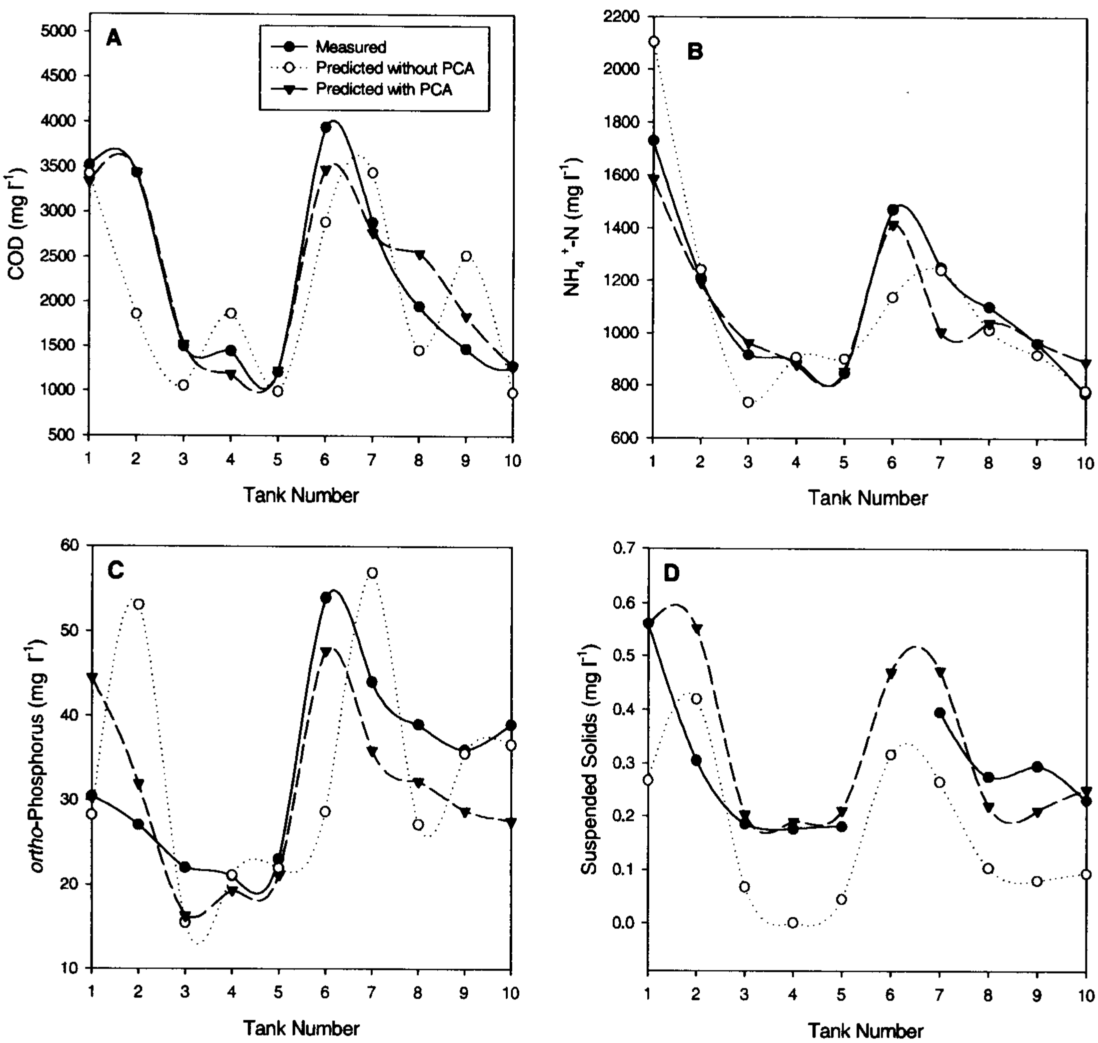

Figure 6. Prediction of various treatment parameters COD (A), NH_4^+—N (B), *o*-P (C) and SS (D) by the neural network modeling. The numbers (1–5) on the *X*-axis represent the influent tank, fermentation tank, aeration tank, sedimentation tank A and sedimentation tank D of day 46, respectively while the numbers (6–10) represent the five equivalent tanks of day of 47 in order.

results when the PCA filtration was used and not used. The scaled mean square errors were calculated based upon Equation (1)

$$\text{scaled MSE} = \frac{1}{N}\sum_{i=1}^{N}(t_i - Y_i)^2 \qquad (1)$$

where $i = 1, 2 \ldots N$ indicate each tank as described above. t_i and y_i are scaled target and scaled prediction results of the proposed neural network, respectively. The scaled data were obtained by the following equation.

$$u = \frac{(x - f_1)}{f_2} \qquad (2)$$

where u means scaled result, and x is real data before the scaling. f_1 and f_2 are constant scaling factors. As shown in Figure 6, the proposed neural network using PCA could predict more accurately than the neural network without going through PCA.

Conclusions

In this paper, we have proposed a novel monitoring system of a piggery slurry recycling treatment process. Multi-layer neural networks combined with PCA successfully modeled the tank characteristics. It was possible to train the neural network with the given data by reducing the input dimension with minimal loss of information and removing the noisy data with one-to-many mapping property. The proposed model may be useful to develop a reverse neural network model that could be used to determine optimal microbial densities critical for a successful treatment of wastewater. The long-term goal of this study will be to construct a real time monitoring system of the recycling treatment for piggery slurry using a multi-layer neural network with an error back-propagation learning algorithm. The multi-layer neural network will contribute to modeling a complex relationship between the various population densities of microorganisms and treatment efficiency of the recycling treatment system for piggery slurry and possibly other livestock wastewaters.

Acknowledgements

We thank Mr. Hun-Jong Lee at Kimhae Piggery Slurry Treatment Plant (Kimhae, Kyungnam, Korea) for providing fresh piggery slurry. This work was supported by the Korea Research Foundation (Grant #1998-024-G-00041).

References

American Public Health Association, American Water Works Association & Water Environment Federation. 1992 *Standard Methods for the Examination of Water and Wastewater*. pp. 2(53)–5(9). Washington, DC: American Public Health Association. ISBN 0-87553-207-1.

Anderson, I.C., Poth, M., Homstead, J. & Burdige, D. 1993 A comparison of NO and N_2O production by the autotrophic nitrifier *Nitrosomonas europaea* and the heterotrophic nitrifier *Alcaligenes faecalis*. *Applied and Environmental Microbiology* **59**, 3525–3533.

Barto, A.G., Sutton, R.S. & Anderson, C.W. 1983 Neuronlike adaptive elements that can solve difficult learning control problems. *IEEE Transactions on Systems, Man and Cybernetics Part B* **13**, 834–846.

Baum, E.B. & Hausser, D. 1989 What size net gives valid generalization? *Neural Information Processing Systems* **1**, 81–90.

Bond, P.L., Erhart, R., Wagner, M., Keller, J. & Blackall, L.L. 1999 Identification of some of the major groups of bacteria in efficient and inefficient biological phosphorus removal in activated sludge systems. *Applied and Environmental Microbiology* **65**, 4077–4084.

Choi, J.H., Chung, Y.R. & Koh, S.C. 1999 Microbial treatment of swine wastewater by recycling reactor system with sequential oxic and anoxic conditions. In *Abstracts of Korea Environmental Engineering Society*. pp. 591–592. Seoul: Korea Environmental Engineering Society. ISSN 1225-5025.

Choi, J.H., Shon, J.I., Yang, H.S., Chung, Y.R., Lee, M. & Koh, S.C. 2000 Modeling of recycling oxic and anoxic treatment system for swine wastewater using neural networks. *Biotechnology and Bioprocess Engineering* **5**, 355–361.

Cote, M., Grandjean, B.P.A., Lessard, P. & Thibault, J. 1995 Dynamic modeling of the activated sludge process: improving prediction using neural networks. *Water Research* **29**, 995–1004

Henze, M., Grady, C.P.L., Gujer, W., Marais, G.V.R. & Matsuo, T. 1987 Activated Sludge Model No. 1. Scientific and Technical Reports No. 1. IAWPRC, London.

Hiraishi, A., Ueda, Y. & Ishihara, J. 1998 Quinone profiling of bacterial communities in natural and synthetic sewage activated sludge for enhanced phosphate removal. *Applied and Environmental Microbiology* **64**, 992–998.

Hornik, K. 1991 Approximation capabilities of multi-layer feed forward networks. *Neural Networks* **4**, 251–257.

Koh, S.C., Bowman, J.P. & Sayler, G.S. 1993 Soluble methane monooxygenase production and trichloroethylene degradation by a type I methanotroph, *Methylomonas methanica* 68-1. *Applied and Environmental Microbiology* **59**, 960–967.

Krieg, N.R. & Gerhardt, P. 1994 Solid, liquid/solid, and semisolid culture. In: *Methods for General and Molecular Bacteriology*. eds. Gerhardt, P., Murray, R.G.E., Wood, W.A. & Krieg, N.R., pp. 216–223. Washington, DC: American Society for Microbiology. ISBN 1-55581-048-9.

Lee, D.S. & Park, J.M. 1999 Neural network modeling for on-line estimation of nutrient dynamics in a sequentially-operated batch reactor. *Journal of Biotechnology* **75**, 229–239.

Lee, D.S. & Park, J.M. 2000 Modeling for industrial wastewater treatment process using hybrid neural networks. In: *Abstracts of Korea Society of Biotechnology and Bioengineering*. pp. 125–128. Taejon: Korea Society of Biotechnology and Bioengineering. ISSN 1225-7117.

Lee, M., Lee, S.Y. & Park, C.H. 1992 Neural controller of nonlinear dynamic systems using higher order neural networks. *Electronics Letters* **28**, 276–277.

Liao, C.M., Maekawa, T., Chiang, H.C. & Wu, C.F. 1993 Removal of nitrogen and phosphorus from swine wastewater by intermittent aeration processes. *Journal of Environmental Sciences and Health B* **28**, 335–374.

Morgan, D. & Scofield, C. 1991 *Neural Networks and Speech Processing*. Boston: Kluwer Academic Publishers. ISBN 0-792-391446-0.

Otte, S., Grobben, N.G., Robertson, L.A., Jetten, M.S.M. & Kuenen, J.G. 1996 Nitrous oxide production by *Alcaligenes faecalis* under transient and dynamic aerobic and anaerobic conditions. *Applied and Environmental Microbiology* **62**, 2421–2426.

Papen, H., Berg, R., Hinkel, I., Thoene, B. & Rennenberg, H. 1989 Heterotrophic nitrification by *Alcaligenes faecalis*: NO_2^-, NO_3^-, N_2O, and NO production in exponentially growing cultures. *Applied and Environmental Microbiology* **55**, 2068–2072.

Shin, H.S., Koo, J.K., Kim, J.O., Shin, H.K. & Jeong, Y.K. 1990 Management alternatives of livestock wastes for water resources conservation. *Journal of Korea Solid Waste Engineering Society* **7**, 45–52.

Simon, H. 1999 *Neural Networks: A Comprehensive Foundation*. pp. 156–173. Prentice Hall Publishing Co. ISBN 0-13-908385-5.

Weigend, A.S. & Gershenfeld, N.A. 1994 *Time Series Prediction: Forecasting the Future and Understanding the Past*. New York: Addison-Wesley Publishing Co. ISBN 0-201-626012.

Zhao, H., Hao, O.J., Fellow, A.S.C.E., McAvoy, T.J. & Chang, C.H. 1997. Modeling nutrient dynamics in sequencing reactor. *Journal of Environmental Engineering* **123**, 863–879.

World Journal of Microbiology & Biotechnology
(2003), 19:21-27