Modeling of Activated Sludge Process Using Various Nonlinear Techniques: A Comparison Study

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Abstract

This paper presents a comparison study between radial basis function neural network (RBFNN), feed forward multilayer perceptron neural network (MLPNN) and adaptive neuro-fuzzy (ANFIS) technique to model the activated sludge process (ASP). All of these techniques are based on the nonlinear autoregressive with eXogenous input (NARX) structure. The ASP inputs and outputs data are generated from activated sludge model 1 (ASM1). This work will cover the dissolved oxygen (DO), substrate and biomass modeling. The performances of the model are evaluated based on R^2, mean square error (MSE) and root mean square error RMSE. The simulation result shows that ANFIS with NARX structure given a better performance compared with the other modeling techniques.

Keywords: ASP; NARX; MLPNN, RBFNN, ANFIS

Introduction

Activated sludge process (ASP) is widely used in waste water treatment plant (WWTP). This process is a multivariable and it has a nonlinear characteristic. Obtaining a good model with simpler structure is demanded because the simplified model can be used for the plant performance prediction and model based control. By nature, the ASP model is highly nonlinear with multivariable parameters. However, the existing ASM model in [1] is too complex. The developed model included too many biological parameters that need to be calibrated and consider [2]. Thus, reliable and simple model are needed for prediction ASP in WWTP system.

Many works was attempted in order to produce high accuracy as an alternative to ASM model likes [3] that used neural network to model the full scale ASP in WWTP. [4] used optimized support vector machine (SVM) as the alternative model for ASP. A few works by Gaya et. al [5][6][7] model the ASP process for WWTP using ANFIS and feed forward neural network technique. The application of self organizing fuzzy neural network was introduce by [8] to model chemical oxygen demand (COD) for ASP in WWTP. The same group developed a self organizing RBF neural network to model the ASP in and further work in [9] shows that the model is capable to be used in predictive control[2].

In this work, RBFNN, MLPNN and ANFIS are chosen with NARX structure and will be applied to model a multivariable ASP. The modeling results are evaluated based on standard model evaluation method techniques which are R^2, mean square error (MSE), root mean square error (RMSE).

Methods

Data Collection

The simulation works was done by applying random signal to the ASP simulator. The system has two inputs (airflow rate and dilution rate) and four outputs ($X_{B,H,}$ is the heterotrophic biomass, S_S is the substrate, S_O is the dissolved oxygen, $X_{B,H,r}$ is the recycled biomass.). The data then is divided into training and testing (prediction) set. In this work, 50% data for training and another 50% data for testing are used. Figure 1 shows the inputs data while Figure 2 presents four output signals from the ASP simulator.

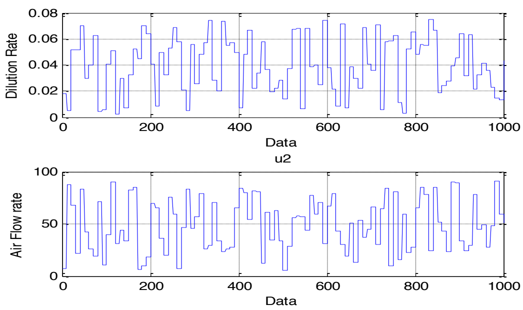

Figure 1 Inputs of the ASP plant

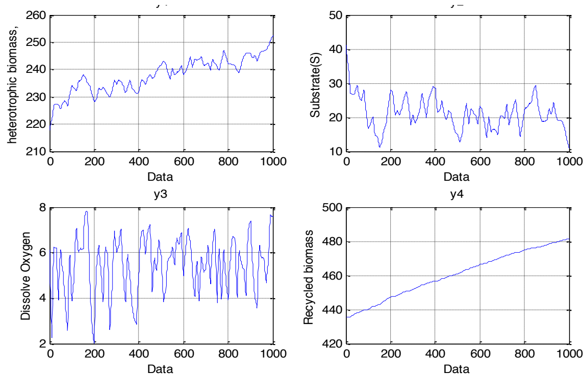

Figure 2 Inputs of the ASP plant

Model Development

The NARX structure was employed in the model development where the selected lag from input outputs variables is train using three different modeling technique such as MLPNN, RBFNN and ANFIS. The result was evaluated using three performance indicators which are R^2, mean square error (MSE), root mean square error (RMSE).

Results and Discussion

From the simulation result it shows all modeling techniques are capable to model the ASP process. Heterotrophic modeling the training simulation results are shown in Figure 3. However, based in the performance evaluation criteria, ANFIS model gives superior performance compared with the others for both training and testing. Figure 4 shows the $X_{B,H}$ testing result.

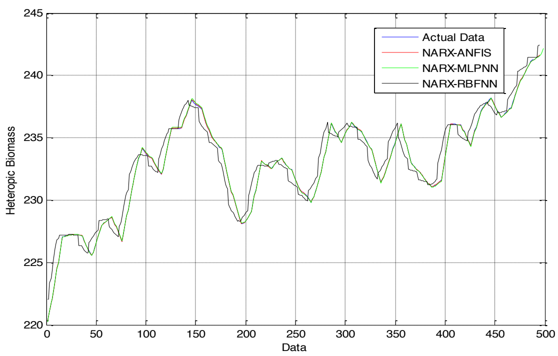

Figure 3 Training result for $X_{H,B}$

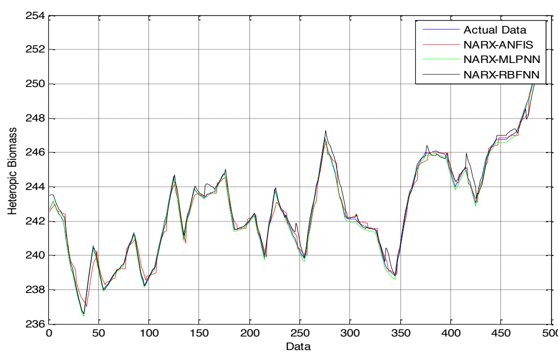

Figure 4 Testing result for $X_{H,B}$

In term of the individual performance criteria as shown in Table 1, ANFIS has better R^2 training followed by MLPNN and RBFNN. For MSE and RMSE, ANFIS has better prediction compare with MLPNN and RBFNN.

Table 1. $X_{H,B}$ Model Evaluation

Training			
	R^2	MSE	RMSE
NARX-ANFIS	99.9942	8.9305e-4	0.0299
NARX-MLPNN	99.9802	0.0032	0.0563
NARX-RBFNN	99.6822	0.0492	0.2219
Testing			
	R^2	MSE	RMSE
NARX-ANFIS	99.7631	0.0220	0.1484
NARX-MLPNN	99.3180	0.0625	0.2500
NARX-RBFNN	98.8187	0.1083	0.3291

In substrate modeling, the same performance was observed which ANFIS model give the higher accuracy. However, the MLPNN also shows a good modeling performance in training and testing where the residuals are almost similar with the ANFIS model. Based on the simulation result, the all the methods give R^2 more than 99%. Only for RBFNN testing result gives only 76.0251%. Full performances of Ss are shown in Table 2.

Table 2. S_S Model Evaluation

Training			
	R^2	MSE	RMSE
NARX-ANFIS	99.9980	3.9819e-6	0.0020
NARX-MLPNN	99.9975	4.4540e-4	0.0211
NARX-RBFNN	99.7297	0.0601	0.2452
Testing			
	R^2	MSE	RMSE
NARX-ANFIS	99.9923	9.0178e-4	0.0300
NARX-MLPNN	99.9897	8.8947e-2	0.0889
NARX-RBFNN	76.0251	2.7992	1.6460

Training and testing result for DO shows a great performance for using ANFIS and MLPNN with both of the techniques give more than 99% R^2. MSE and RMSE result shows very minimum error for training and testing. However, the RBFNN give poor R^2 value for DO testing. Summary of the performances of the training and testing result are presented in Table 3.

Table 3. DO Model Evaluation

Training			
	R^2	MSE	RMSE
NARX-ANFIS	100.000	4.3175e-7	6.5707e-4
NARX-MLPNN	99.8209	0.0023	0.0479
NARX-RBFNN	97.9523	0.0353	0.1880
Testing			
	R^2	MSE	RMSE
NARX-ANFIS	99.9697	2.5321e-4	0.0159
NARX-MLPNN	99.7178	0.0031	0.0554
NARX-RBFNN	66.8685	0.2768	0.5261

The simulation results for $X_{H,B,r}$ shows that the ANFIS with NARX structure give almost identical result with NARX-MLPNN. However, ANFIS has smallest error compared with MLPNN. The RBFNN has significant residual for training and testing simulation. Table IV shows the modeling performance of $X_{H,B,r}$.

Table 4. $X_{H,B,r}$ Model Evaluation

Training			
	R^2	MSE	RMSE
NARX-ANFIS	99.9998	1.1574e-4	0.0108
NARX-MLPNN	99.9993	4.1537e-4	0.0204
NARX-RBFNN	99.5338	0.2694	0.5190
Testing			
	R^2	MSE	RMSE
NARX-ANFIS	99.9253	0.0246	0.1567
NARX-MLPNN	99.7607	0.0756	0.2749
NARX-RBFNN	98.6404	0.4473	0.6688

Conclusion

This work presented the comparisons study of ASP modeling using ANFIS, MLP and RBF neural network based on the NARX structure. The data is divided based on first 50% for training and the last 50% for testing. Performances of the modeling techniques are follow several criterions which are R^2, MSE and RSME. The result shows ANFIS with NARX structure gives the higher fitting value and less error for training and testing simulation. However, MLPNN can also be very reliable model prediction for all outputs. However, RBFNN in the simulation results has shows some noticeable deviation even though the output paten stills similar with the actual output, it might be caused by insufficient training data

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