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Modelling and Evaluation of Sequential Batch Reactor Using Artificial Neural Network

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ABSTRACT

The main objective of wastewater treatment plant is to release safe effluent not only to human health but also to the natural environment. An aerobic granular sludge technology is used for nutrient removal of wastewater treatment process using sequential batch reactor system. The nature of the process is highly complex and nonlinear makes the prediction of biological treatment is difficult to achieve. To study the nonlinear dynamic of aerobic granular sludge, high temperature real data at 40˚C were used to model sequential batch reactor using artificial neural network. In this work, the radial basis function neural network for modelling of nutrient removal process was studied. The network was optimized with self-organizing radial basis function neural network which adjusted the network structure size during learning phase. Performance of both network were evaluated and compared and the simulation results showed that the best prediction of the model was given by self-organizing radial basis function neural network.

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1. INTRODUCTION

An aerobic granular sludge (AGS) technology has been used widely for nutrient removal process using sequential batch reactor (SBR) system [1]. The advantages of AGS using SBR are because of the stability and flexibility, the low requirement of energy level, the increase in biomass concentration, the presence of aerobic and anoxic process in the same system and the reduction in operational cost [2]. SBR treats wastewater in a batch treatment process which means, each of the process occurs sequentially in a single reactor basin. The flexibility of SBR process makes it applicable for all types of wastewater and plant capacity for biological treatment [3]. Modelling nutrient removal processes using SBR involves physical, biological and chemical processes. Due to this nature, the system exhibits nonlinearity, complexity and dynamic behavior [4]. The use of artificial neural network (ANN) has shown a promising result in various engineering application, pattern recognition and financial market analysis [4]. Some of the features of neuron-based approach are simplicity, fault and noise tolerance as explained in [5]. A number of research has confirmed that ANN offers a better solution in modelling wastewater treatment plant (WWTP). Due to the significant characteristic of ANN in approximating complex and nonlinear system, it is capable of achieving high accuracy without the needs to understand the rules governing complex biological reactions [5].

The work presented in [4] showed a better prediction of effluent concentration of biological oxygen demand (BOD) and suspended solid (SS) in the final clarifier tank using feed-forward neural network (FFNN). The model achieved a good fit for the measured BOD and SS data. An ANN black-box modelling application was also applied at Doha West WWTP in state of Qatar [5] to study and analyze the

interdependency of input-output variables. FFNN with single input and multi input topologies were utilized to examine the relation of influent and effluent parameters. From the results, a better prediction of chemical oxygen demand (COD), BOD and SS effluent concentration were achieved when COD of the crude supply stream was used as an input to the network. Another example of ANN application was presented in [3]. The modelling of biological removal of organic Carbon and Nitrogen was implemented on slaughterhouse wastewater treatment. The aim of this work was to identify the best operation conditions for a cycle for the treatment requirement. The ANN structure used was a three-layered FFNN with backpropagation training algorithm which consists of six inputs, a hidden layer with the same neurons of the input layer and two outputs. The results indicated that the ANN models able to provide efficient prediction for SBR performance.

FFNN is a powerful tool for approximating continuous function and it has been proved in [3]-[5]. However, recurrent neural network (RNN) also proved that it has more capability for prediction of dynamic system as compared to FFNN [6]. The network has an internal feedback on the second hidden layer. The dynamic properties was introduced to form a dynamic network to predict BOD concentration. The experimental results indicated that modelling RNN was more efficient as compared to FFNN. Another application of RNN was implemented in [7]. The network output was used as feedback to the input layer for the subsequent time step. The objective of this work was to model SS and volatile suspended solids concentration. The simulation results showed that the prediction of the proposed model was better than the mechanistic model developed by Sun.

Another ANN topology used in wastewater treatment modelling is radial basis function neural network (RBFNN). RBFNN structure has only one layer of hidden layer and the hidden nodes implement a set of radial basis function that are radially symmetric. Normally, Gaussian activation function with the radius and center parameters are defined separately at each RBF unit [8]. The output nodes implement linear summation function. The advantages of RBFNN over FFNN and RNN are mentioned in [8] such as faster convergence, smaller training errors and higher reliability. The aim of work presented in [8] was to evaluate performance of a submerged membrane bioreactor treating combined municipal and industrial wastewater. The evaluation of effluent quality parameters was modelled using RBFNN. The training and testing prediction were very close to the experimental data. With coefficient of determination higher than 0.98 and root mean square less than 7%, this indicated that RBFNN modelling was quite efficient. A comparison of RBFNN and FFNN performance was also conducted in [9]. Both networks were developed to study the effects of influent concentration, filling time, reaction time, aeration intensity, solids retention time and mixed liquor volatile suspended solids concentration on the effluent concentration of total suspended solids, total phosphorus (TP), COD and NH4+-N using SBR. RBFNN demonstrated a good performance with consideration of more inputs to the network.

An enhancement of RBFNN was implemented in [10] to capture the BOD concentration of WWTP. A growing and pruning algorithm was presented which was named as self-organizing radial basis function network (SORBFNN). The network was able to adjust the number of hidden neurons automatically during training phase. The final structure of the proposed model was analyzed online and it was observed that the model performance was better in terms of CPU time, testing error and the final number of hidden nodes. The same network was also applied in [11] to model dissolved oxygen concentration in activated sludge WWTP. The capability of the SORBFNN model in model predictive control for the system was studied. The developed model showed that an accurate prediction had been achieved. The ability to update hidden nodes of the RBF increased the network accuracy to adapt to nonlinear dynamic system. Another application of SORBFNN was found in [12] for prediction of activated sludge bulking. The aim of this study to predict the sludge volume index evolution. The advantage of the proposed model was the ability to simplify and accelerate the structure thus, giving a better prediction of sludge volume index.

2. RESEARCH METHOD

In this work, the main objective is to model SBR using RBFNN and to introduce self-organizing algorithm in the RBFNN structure to enhance the prediction accuracy. Self-organizing algorithm allows the network structure to grow or prune with respect to the data.

2.1. Radial Basis Function Neural Network

The basic of RBFNN architecture comprises of three layers: an input layer, a hidden layer and an output layer. The network structure of proposed RBFNN consist of six input nodes, six hidden nodes and one output node. The concentration of influents such as chemical oxygen demand (COD), total organic carbon (TOC), total nitrogen (TN), total phosphorus (TP), ammonia nitrogen (AN), and mixed liquor suspended solids (MLSS) are the input to the network for prediction of TN, TP or AN effluent. These input and output

parameters are used to train RBFNN network. The experimental data contains 21 real data points at temperature of 40˚C.

The output of the proposed network, y with K number of hidden nodes are calculated as Equation (1) where $\boldsymbol{x}$ represents the input of the network, $\boldsymbol{x} = (x_{COD}, x_{TOC}, x_{TP}, x_{TN}, x_{AN}, x_{MLSS})^T$, with weights, w_k at output layer and $\theta_k(\boldsymbol{x})$ is the output of Gaussian function as described in Equation (2).

$$y = \sum_{k=1}^{K} w_k \, \theta_k(\boldsymbol{x}) \tag{1}$$

$$\theta_k(\boldsymbol{x}) = e^{||\boldsymbol{x}-\mu_k||/\sigma_k^2} \tag{2}$$

The value of μ_k and σ_k denote the value of center and radius of each RBF unit respectively. $||\boldsymbol{x} - \mu_k||$ is the Euclidean distance between $\boldsymbol{x}$ and μ_k.

Radially symmetric basis function is used as an activation function which mapping the input nodes to the hidden nodes nonlinearly. Thus, the training of center and radius of each RBF unit are conducted by an unsupervised learning [8]. For the unit center, K-means clustering algorithm is selected to determine the parameter of hidden neurons. The standard steps for obtaining center and radius are described as follow:

1. The center of each RBF unit is initialized randomly with respect to the training data. The value of each center must be different from each other.
2. Calculate Euclidean distances between training data and the centers of each RBF and assign each of the training data is assigned to the nearest value of the centers.
3. New RBF centers are calculated based on the average center for each cluster in step (2).
4. Go to steps (2) and (3), until the RBF centers remain unchanged for the subsequent iterations.
5. When RBF centers have been determined, the radius is calculated using K-nearest neighbors algorithm as Equation (3):

$$\sigma_k = \sqrt{\frac{\sum_{i=1}^{k}(c_j - c_i)^2}{k}} \tag{3}$$

The training method of the weights at the output layer are conducted in supervised learning [8]. This is achieved by simply manipulating Equation (1) in a matrix form as shown in Equations (4) and (5).

$$y = wH \tag{4}$$

$$w = (H'H)^{-1}H'y \tag{5}$$

Figure 1 summarizes the flow of RBFNN algorithm. In the beginning, data pre-processing is applied to the database. The network initialization starts with determination of the hidden layer parameters which are the radius and the center of Gaussian function. Then, it is proceed with determination of weights at output layer. After that, weight adjustment is executed. Once, training phase completed it will be followed by network evaluation.

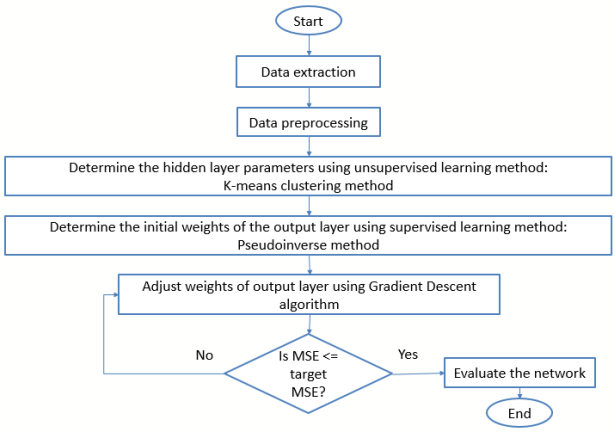

Figure 1. Flowchart of RBFNN algorithm

2.2. Self-organizing Radial Basis Function Neural Network

In SORBFNN, the hidden nodes are updating its structure based on rate node activity (NA) and the mutual information (MI). The follow explanation of node adjusting and splitting mechanism is based on the proposed method in [11] and [12], and it is implemented in this work. Calculation of MI is based on Equation (6) which having information of statistical dependence between random variable where $p(\theta_i, Y)$ is the joint distribution, $p(\theta_i)$ and $p(Y)$ are the probability density function, θ_i is the output of ith hidden node and Y is the network's output.

$$M(\theta_i: Y) = \sum_{\theta,y} p(\theta_i, Y) log_2 \frac{p(\theta_i,Y)}{p(\theta_i)p(Y)} \quad (6)$$

The Equation (7) also can be interpret in terms of their Shannon entropy $H(\theta_i)$ and $H(Y)$. The MI is positive and equal zero if θ_i and Y are statistically independent.

$$M(\theta_i: Y) \leq \min(H(\theta_i), H(Y)) \quad (7)$$

This bound (Equation (7)), taking together with $M(\theta_i: Y) \geq 0$, tells that the normalized MI, $m(\theta_i: Y)$ is as in Equation (8) where $0 \leq m(\theta_i: Y) \leq 1$.

$$m(\theta_i: Y) = \frac{M(\theta_i:Y)}{\min(H(\theta_i),H(Y))} \quad (8)$$

In the network structure of RBFNN, the connection is deleted if normalized MI value is zero as it indicates that the node i and Y are independent. For splitting node case, the NA is calculated as in Equation (9) where NA_i is the active firing of the ith hidden node, m_i is the MI value of the ith hidden node, and θ_i is the output value of the ith hidden node.

$$NA_i = m_i |w_i \sqrt{\theta_i(x)} \quad (9)$$

If NA is greater than threshold NA, the hidden nodes will be split into few nodes. The centers and the radiuses of the new divided hidden nodes are explained in Equations (10) and (11) where $0.95 < \alpha_j < 1.05$ and $0 < \beta_j < 0.1$, μ_i and σ_i are the center and radius of the ith hidden node, and N_{new} is the number of the new divided nodes to be decided by the rate of average firing as Equation (12).

$$\mu_{i,j} = \alpha_j \mu_i + \beta_j x, \quad (10)$$

$$\sigma_{i,j} = \alpha_j \sigma_i, \quad j = 1, 2, \dots, N_{new} \quad (11)$$

$$Af_i = \frac{1}{\|x-\mu_i\|+\tau} \frac{\theta_i(x)}{\sum_{i=1}^{K} \theta_i(x)}, \quad (i = 1, 2, \dots, K) \quad (12)$$

The weights for the new nodes and the output layer are updated based on Equations (13) and (14) where ζ is the allocating parameters for the new nodes, $\theta_i(t)$ is the output value of the ith hidden node, $\theta_{i,j}(t)$ is the output value of the new divided jth hidden node, w_i is the weight of the ith hidden node, $e(t)$) is the current approximation error of the RBFNN (Equation (15)),and $y(t)$ is the output of the neural network and $\hat{y}(t)$ is the system output for the current sample x at time t.

$$w_{i,j} = \zeta_j \frac{w_i.\theta_i(t)-e(t)}{N_{new}.\theta_{i,j}(t)}, \quad (13)$$

$$\sum_{j=1}^{N_{new}} \zeta_i = 1, j = 1, 2, \dots, N_{new} \quad (14)$$

$$e(t) = \hat{y}(t) - y(t), \quad (15)$$

The summary of SORBFNN is illustrated in Figure 2. A working RBFNN network with five hidden nodes is established first before calculating MI. If MI less then threshold MI, the connection will be deleted. Else, NA will be examined. If NA higher than threshold NA, the connection will be divided into two nodes.

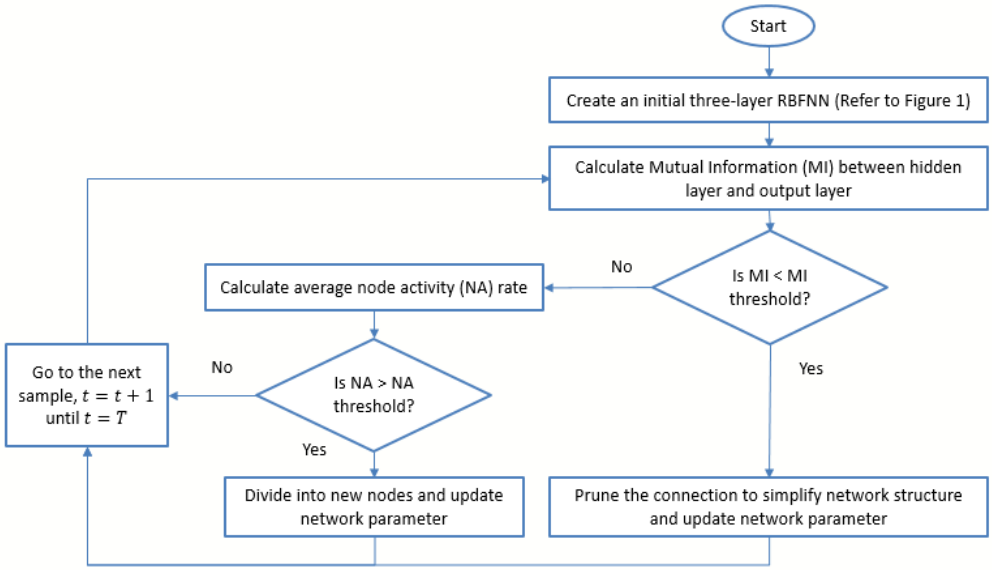

Figure 2. Flowchart of SOFRBNN

3. RESULTS AND ANALYSIS

For RBFNN, the network consist of three layers which were input, hidden and output layer. It was designed based on the number of hidden neurons given by user. The network parameter of hidden and output layer were determined separately using different method. The training of hidden layer was implemented using unsupervised learning method. In unsupervised learning method, output was not necessarily needed and the learning was dependent mainly on input data. The center and radius of each radial basis function unit were determine using K-means clustering algorithm to find the best centers with respect to the input data. All radius values were defined as 0.5 for simplicity since radius did not affect much on the performance. The weights at output layer, were determined using supervised learning method. In contrast to unsupervised learning method, supervised learning method required output data. The learning method was realized using Pseudoinverse technique. After all RBFNN parameters were initialized, the weights were further adjusted using Gradient Descent algorithm which helped to improve network performance by reducing output error.

SORBFNN algorithm was an enhancement of RBFNN algorithm. The way SORBFNN adapted to the changes was by adjusting the network size on its own. Initially, a working RBFNN with five hidden neurons was needed to be established. As the data sample introduced to the network, SORBFNN started to calculate MI at each RBF unit. The smallest MI will be compared with threshold MI. The connection will be deleted if the value was less than threshold value. For the remaining RBF unit, NA will be further evaluated. The higher NA rate will be selected and compared with threshold NA. If the calculated NA was greater than threshold NA, the connection will be divided into two nodes.

Figure 3 shows the TP prediction during training and testing phase. In training phase, SORBFNN only scores 0.0284 of MSE value as compared to RBFNN which is 0.0148. The value of R^2 for SORBFNN is 0.8788 while for RBFNN is 0.9367. However in testing phase, SORBFNN achieves better MSE with 0.0313 and R^2 with 0.8442. The detail of TP performance is shown in Table 1.

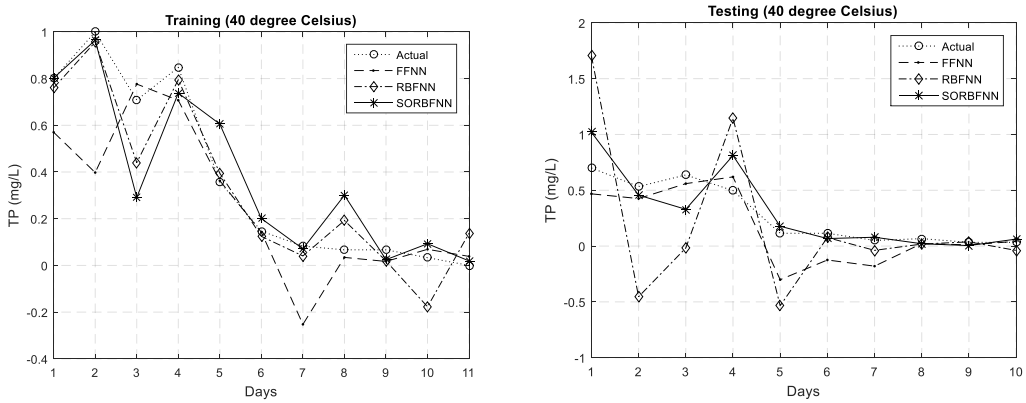

Figure 3. Comparison of FFNN, RBFNN and SORBFNN modelling for TP

Table 1. Performance result for TP

	Training		
	MSE	MAD	R^2
FFNN	0.0508	0.2750	0.7829
RBFNN	0.0148	0.3040	0.9367
SORBFNN	0.0284	0.2937	0.8788
	Testing		
	MSE	MAD	R^2
FFNN	0.0372	0.2911	0.8146
RBFNN	0.3273	0.4942	-0.6300
SORBFNN	0.0313	0.2812	0.8442

The performance of TN estimation as depicted in Figure 4. The training result indicates that RBFNN has better accuracy than SORBFNN with MSE 0.0104 and 0.0245 respectively. The value of R^2 for SORBFNN is 0.8901 while for RBFNN is 0.9534. Meanwhile, SORBFNN gives good estimation over RBFNN with MSE and R^2 value are 0.0569 and 0.7282 (refer Table 2).

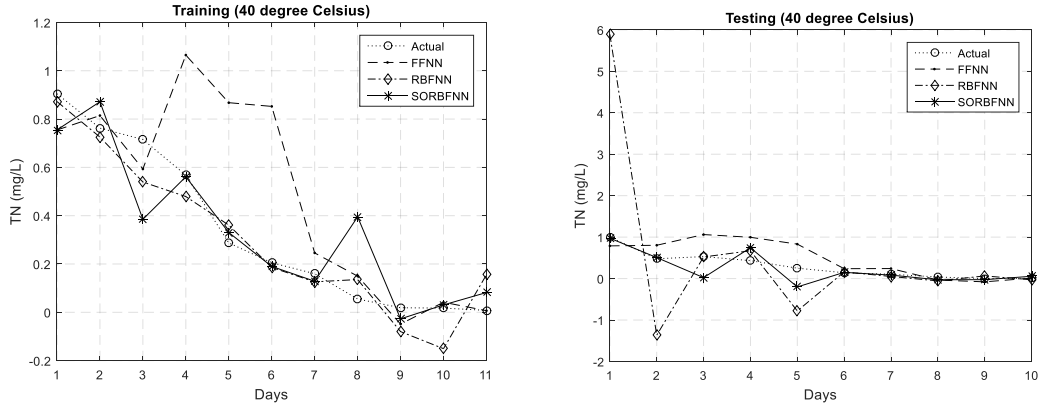

Figure 4. Comparison of FFNN, RBFNN and SORBFNN modelling for TN

Table 2. Performance result for TN

	Training		
	MSE	MAD	R^2
FFNN	0.0968	0.3697	0.5666
RBFNN	0.0104	0.2645	0.9534
SORBFNN	0.0245	0.2337	0.8901
	Testing		
	MSE	MAD	R^2
FFNN	0.1128	0.4104	0.4612
RBFNN	2.8466	1.1092	-12.6007
SORBFNN	0.0569	0.3083	0.7282

In AN approximation as in Figure 5, SORBFNN demonstrates good approximation for both training and testing phases compared to RBFNN and FNN. MSE and R^2 value during training for SORBFNN are 0.0168 and 0.9195 while for RBFNN are 0.0191 and 0.9084. Approximation for AN during testing phase was difficult to achieved. Therefore the result in Table 3 show that error for FFNN, RBFNN and SORBFNN are quite huge. RBFNN and SORBFNN give similar result with MSE 0.1308 and R^2 0.2833.

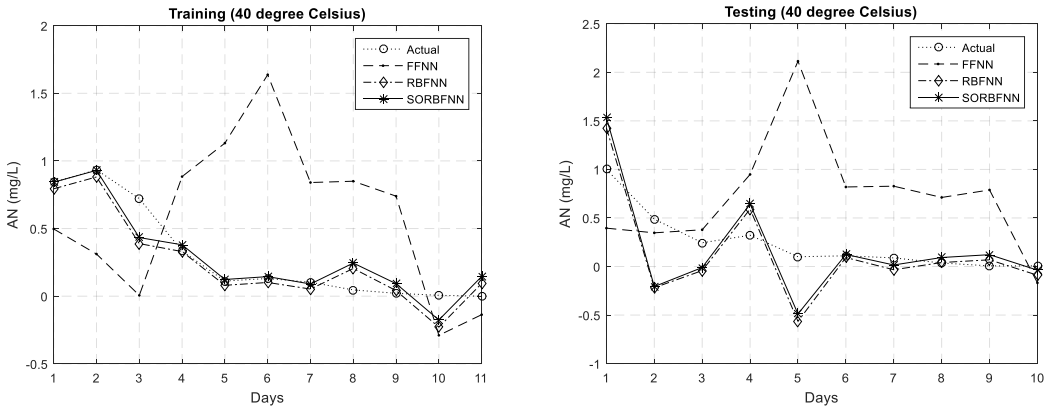

Figure 5. Comparison of FFNN, RBFNN and SORBFNN modelling for AN

Table 3. Performance result for AN

	Training		
	MSE	MAD	R^2
FFNN	0.5855	0.4642	-1.8120
RBFNN	0.0191	0.2542	0.9084
SORBFNN	0.0168	0.2552	0.9195
	Testing		
	MSE	MAD	R^2
FFNN	0.6999	0.3835	-2.8336
RBFNN	0.1308	0.3528	0.2837
SORBFNN	0.1308	0.3642	0.2833

In this section, it is explained the results of research and at the same time is given the comprehensive discussion. Results can be presented in figures, graphs, tables and others that make the reader understand easily [2],[5]. The discussion can be made in several sub-chapters.

4. CONCLUSION

This paper presents the modelling of SBR using RBFNN and SORBFNN. SORBFNN has a capability of growing and pruning the network structure in learning phase to adapt with the data behavior. The results indicate that SORBFNN has high potential in estimating nutrient removal process. The error estimation in testing phase for SORBFNN is much lower as compared to RBFNN. However, an improvement is needed to be considered in future work to get a better coefficient determination of the prediction.

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