Prediction of standard aeration efficiency of a propeller diffused aeration system using response surface methodology and an artificial neural network

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ABSTRACT

Aeration experiments were conducted in a masonry tank to study the effects of operating parameters on the standard aeration efficiency (SAE) of a propeller diffused aeration (PDA) system. The operating parameters included the rotational speed of shaft (N), submergence depth (h), and propeller angle (α). The response surface methodology (RSM) and an artificial neural network (ANN) were used for modelling and optimizing the standard aeration efficiency (SAE) of a PDA system. The results of both approaches were compared for their modelling abilities in terms of coefficient of determination (R²), root mean square error (RMSE), and mean absolute error (MAE), computed from experimental and predicted data. ANN models were proved to be superior to RSM. The results indicate that for achieving the maximum standard aeration efficiency (SAE), N, h and α should be 1,000 rpm, 0.50 m, and 12°, respectively. The maximum SAE was found to be 1.711 kg O₂/kWh. Cross-validation results show that best approximation of the optimal values of input parameters for maximizing SAE is possible with a maximum deviation (absolute error) of ±15.2% between the model predicted and experimental values.

Key words: aquaculture, operating parameters, propeller diffused aeration system, standard aeration efficiency

HIGHLIGHTS

• Aeration characteristics of a propeller diffused aerator (PDA) were evaluated.
• The response surface methodology (RSM) and an artificial neural network (ANN) were used for modelling and optimizing the standard aeration efficiency (SAE) of a PDA system.
• The results of RSM and ANN were compared for their modelling abilities in terms of coefficient of determination (R²), root mean square error (RMSE) and mean absolute error (MAE), computed from experimental and predicted data.

1. INTRODUCTION

Aeration is an important factor in aquaculture. The level of dissolved oxygen (DO) concentration in aquaculture systems sometimes may fall below the critical level (less than 5 mg/L) and may lead to mortality of aquatic animals. Therefore, the water of an aquaculture system is required to be aerated to maintain the desired level of DO in the system. Many types of aeration systems e.g., mechanical, diffused-air, gravity, etc., have been developed over time and are currently in use in aquaculture operations (Boyd 1998; Moulick et al. 2002, 2005; Boyd & Hanson 2010; Roy et al. 2015, 2017, 2020a, 2020b; Jayraj et al. 2018; Tanveer et al. 2018; Cheng et al. 2019). Aerators are essential in semi-intensive and intensive aquaculture to maintain the physiological requirements of culture organisms. Artificial aeration is very necessary in an intensive fish culture system (Boyd & Watten 1989). The obvious role of aeration is to supply oxygen to aquatic animals. In addition, aeration of the water may influence a variety of other biological parameters in the water body. In the biological treatment of wastewater, aeration is an important process employed to raise the DO level to allow aerobic bacteria to reduce the biochemical oxygen demand of the effluent and thus to improve the water quality. The oxygen supplied must be at a rate sufficient to at least balance the rate of removal of the active biomass. Aerators are the devices used to supply oxygen to meet such demands (Moulick et al. 2010).

The use of aerators as oxygen transfer devices in biological wastewater treatment systems has been very common for decades. Pond aeration systems have become very popular in aquaculture during the past two
decades (Peterson & Walker 2002). The performance evaluation of these aeration systems has been very important in selecting the design features to provide cost-effective and efficient aerators to be used in aquaculture. Paddle wheel aerators and propeller-aspirator-pumps are the most widely used aerators in aquaculture (Boyd 1998). Ruttanagosrigit et al. (1991) reported that propeller-aspirator-pump aeration is more efficient to transfer oxygen to water effectively at a salinity range of 10–30 ppt. The propeller-aspirator-pump aeration has an aeration efficiency approximately 1.5 times greater than the Taiwan paddle wheel aerator at a salinity range of 10–30 ppt. The aeration efficiencies for the propeller-aspirator-aerator and paddle wheel aerator were found to be 1.20 and 0.85 kg O2/kWh, respectively. Boyd & Moore (1993) reported that a propeller diffused aeration (PDA) system performs better in deep water than in shallow water. Boyd & Martinson (1984) used propeller-aspirator-pump aerators of different sizes (0.38, 1.5, and 2.24 kW) in a tank of low water depth of 1.04 m to evaluate performance. The test results showed that the standard aeration efficiency (SAE) value varies from 1.73 to 1.91 kg O2/kWh. Vinatea & Carvalho (2007) conducted aeration experiments on paddle wheel and propeller-aspirator-pump aerators using water of different salinities. The results revealed that the efficiency of the aerators decreases beyond 30 ppt of salinity. Kumar et al. (2010) conducted aeration experiments to evaluate the performance of a propeller-aspirator-pump aerator. The maximum SAE of 0.42 kg O2/kWh was obtained at a positional angle of 75°, rotational speed of 2,840 rpm, and submergence depth of 0.14 m for the propeller shaft.

Recently, soft computing techniques such as Artificial Neural Networks (ANNs), Genetic Algorithm (GA), Support Vector Machine (SVM), and Fuzzy Logic (FL) have been widely used in aeration system modelling. Bagatur & Onen (2014) reported that the capability of Gene Expression Programming (GEP) is tested in relating triangular weir variables with air entrainment rate as well as aeration efficiency. Kumar et al. (2018) applied ANNs for modelling aeration efficiency in weir aerators. Mjalli et al. (2007) proposed a model for predicting the performance of aeration efficiency of wastewater treatment plants using an ANN. ANNs have better generalization ability, less susceptibility to noise and outliers than regression models. However, to the best of our knowledge, no information is available in the literature regarding a comparison of the aeration efficiencies of a PDA system obtained by using response surface methodology (RSM) and ANN modelling techniques.

Recently many statistical experimental design methods are being used in aeration systems to optimize the operating parameters (Roy et al. 2020a). Conventionally, the optimization of a multivariable system follows one factor at a time. Many experiments are required for conventional techniques, and such methods do not represent the combined effect. This also requires more data to determine the optimum level (Mohammadpour et al. 2016). The primary purpose of the experimental design technique is to understand the interactions among the parameters, which could help in the optimization of experimental parameters and provide statistical models. It has been found from the literature that very limited work has been done on statistical optimization of aeration efficiency. Therefore, the present research aimed to investigate the effectiveness of statistical optimization techniques to determine the optimum aeration efficiency of a propeller diffused aerator.

In general, diffused aeration systems are not used in ponds with low depth, since bubbles rise too quickly to get fully absorbed. Hence, the DO in a water body does not increase appreciably. In aquaculture ponds with water volumes less than 10,000 m³, a diffused aeration system is not suitable (Boyd & Moore 1993; Boyd 1998; Roy et al. 2021). Therefore, there is an attempt to design a simple, efficient, and cost-effective aerator. A PDA system is an extension of a diffuser aerator. In a diffuser aeration system, air or oxygen is injected directly into a body of water by a diffuser fixed at the end of an air or oxygen pipeline. The diffuser is placed at the middle of the water body so that the bubble of air or oxygen released from the diffuser moves upward, and oxygen is transferred from the bubbles to the water by diffusion across the liquid film. The rate of oxygen transfer increases with the contact time between the water and the bubbles. The propeller in a PDA system circulates the water along with bubbles downward through a conical hood, thus increasing the contact time of the bubbles and thereby increasing the rate of oxygen absorption of the water body. A propeller diffused aerator aerates water near the surface and transfers the aerated water to the bottom part of the water body. Therefore, a PDA system appears to be quite suitable for intensive aquaculture for aeration of water and also consumes less energy compared to other systems (Boyd 1998).

The aeration characteristic of a propeller diffused aerator depend on different design features of the propeller. These include: (i) rotational speed of the propellers (N), (ii) submergence depth (h) of the propellers, and (iii) propeller angle (α). The variation in rotational speed, submergence depth, and propeller angle are the important parameters which may affect the oxygen transfer rate and aeration efficiency. Many published studies exist for
paddle wheel aerators, propeller-aspirator-pump aerators, diffused aerators, etc.; however, to date, no study has been reported on a PDA system. Therefore, the present research was conducted to optimize the different operating parameters e.g., rotational speed (N), submergence depth (h) of PDA system as well as the propeller angle (α) needed to achieve maximum aeration efficiency.

2. THEORETICAL CONSIDERATIONS

2.1. Overall oxygen transfer coefficient (K*L*a*)

The standard model for oxygen transfer is formulated as a mass balance equation of variation of DO concentration in the water with time and is given by Equation (1) (ASCE 2007):

\[ \frac{dC}{dt} = K_{LaT} \left( C^* - C_0 \right) \]  

where, C (mg/L) is the concentration of oxygen at time t, C* (mg/L) is the equilibrium liquid phase oxygen concentration, C_0 (mg/L) is the initial DO concentration, and K_{LaT} (h^-1) is the overall oxygen transfer coefficient at T °C.

By assuming K_{LaT} constant, the solution of the Equation (1) can also be expressed as:

\[ C = C^* - \left( C^*_0 - C_0 \right) \times \text{Exp} \left[ -K_{LaT} \times t \right] \]  

Nonlinear regression was used to estimate K_{LaT} and C^*_0. These estimates were then adjusted to standard conditions (20 °C water temperature, zero DO concentration and one atmosphere pressure) using Equation (3). K_{LaT} was then converted to K_{La20} (Shelton & Boyd 1983; ACSE 2007; Jiang & Stenstrom 2012) and expressed as:

\[ K_{La20} = \left( K_{La} \right)_T \theta^{T-20} \]  

where, K_{La20} is overall oxygen transfer coefficient at 20 °C (h^-1) and \( \theta \) is the correction factor of temperature and its value is 1.024 for clean water.

2.2. Standard oxygen transfer rate (SOTR) and standard aeration efficiency (SAE)

The two performance measures generally used to evaluate the performance of an aerator are standard oxygen transfer rate (SOTR) and standard aeration efficiency (SAE). The SOTR of an aeration system is defined as the oxygen transfer per unit time to a water body under standard conditions (water temperature: 20 °C, initial DO concentration = 0 mg/L, one atmospheric pressure and clean tap water) (APHA 1992; ASCE 2007) and is given by Equation (4):

\[ \text{SOTR} = \frac{K_{La20}}{C^* - C_0} \times V \times 10^{-3} \]  

where, SOTR is the standard oxygen transfer rate (kg O_2/h), C^* is the DO saturation value (mg/L), C_0 is the initial DO concentration (mg/L), V is the volume of water in the tank, m^3 and 10^{-3} is the factor for converting g to kg.

SAE is a better comparative performance parameter than SOTR (Elliott 1969; Lawson & Merry 1993), and is defined as the SOTR per unit of power input to the aerator and is given by Equation (5):

\[ \text{SAE} (\text{kgO}_2/\text{kWh}) = \frac{\text{SOTR}}{P} \]  

where, P denotes the input power to the aerator (kW).

3. METHODOLOGY

3.1. Experimental setup

The developed propeller diffuser aerator (Figure 1) consists of a 2 HP variable speed D.C. shunt wound type motor for providing power to the aerator (make: Kirloskar Brothers Limited, Kolkata, India). The rpm was measured by using a tachometer. The aerator shaft was made up of 316 grade mild steel. Different propeller angle setups were fabricated using cast iron. The durability of cast iron is greater compared with other materials.
The cast iron sheets were cut as per the designed specifications (Figure 2). The specifications of the propeller are as follows: (i) material—cast iron, (ii) diameter of propeller: 0.152 m, (iii) maximum blade thickness: 5.2 mm, (iv) minimum blade thickness: 3.62 mm, (v) Pitch ratio: 0.8 and (vi) hub diameter: 254 mm. A 25 mm nylon pipe (conduit) of 4 mm diameter was used for the purpose of injecting air into the testing tank at the desired pressure. Nylon pipe was selected because of its durability. As air was injected through the diffuser, the air bubbles started rising through the water column. A conical hood was provided to mix the water with air. The aerator was mounted at the centre of the tank.

### 3.2. Aeration test

Unsteady state aeration tests were conducted in a brick masonry tank of dimensions 3.71 m x 3.71 m x 1.5 m to evaluate the oxygen transfer efficiencies of the aerators following the standard procedure (ASCE 2007). Initially, the water was deoxygenated using 0.1 mg/L of cobalt chloride and 10 mg/L of sodium sulphite for each 1.0 mg/L of DO present in water and for each liter volume of water (Boyd 1998). A minimum two points were used to measure the DO concentration in the tank, one at a shallow depth and one at a deep location. The points should be located at least 0.20 m or more below the water surface (Baylar et al. 2007) in the tank. At least 45 DO readings at equal time (1 min) intervals were taken. The average reading of the DO meters was considered as the DO concentration of water. After experiments, the DO probes were cleaned using distilled water. Finally $K_L\alpha_T$ was estimated using Equation (6) by determining the three parameters, $C_0$, $C^*$, and $K_L\alpha_T$ simultaneously using a nonlinear method (Jiang & Stenstrom 2012):

$$C_t = C^* - (C^* - C_0) \times \exp \left[-K_L\alpha_T \times t\right]$$

Finally $K_L\alpha_T$ was converted to a value at a standard temperature of 20 °C as $K_L\alpha_{20}$, and the values of SOTR and SAE were computed using Equations (1) and (2), respectively.
3.3. Experimental design and statistical analysis

In the present study, the response surface methodology (RSM), using a central composite design (CCD), was adopted for modelling the standard aeration efficiency (SAE) of the developed propeller diffused aerator. The independent operating parameters include the rotational speed of shaft (N), submergence depth (h), and propeller angle (α), whilst SAE was considered as the model response.

With the help of the limiting values of the independent variables, five different levels of coded values, i.e., +α, +1, 0, –1, and –α, were selected (Montgomery 1991). Applying the relationships given in Table 1, the values of the coded variable levels for the CCD were calculated as shown in Table 2. These were then used to determine the actual levels of the variables for each of the 20 experiments. The details of these are presented in Table 3.

The experiments were designed and executed by employing second order polynomial models in order to predict the SAE, in the following form:

\[ Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_1^2 + b_5X_2^2 + b_6X_3^2 + b_7X_1X_2 + b_8X_1X_3 + b_9X_2X_3 \]  

(7)

Figure 2 | Different angles of propeller.

### Table 1 | Relationship between coded and actual values of a variable (Behera et al. 2018)

| Code value | Actual level of variable |
|------------|-------------------------|
| −α         | \( X_{\text{min}} \)     |
| −1         | \( \frac{[x_{\text{max}} + x_{\text{min}}/2] - ([x_{\text{max}} - x_{\text{min}}]/2)}{\beta} \) |
| 0          | \( \frac{x_{\text{max}} + x_{\text{min}}}{2} \) |
| +1         | \( \frac{[x_{\text{max}} + x_{\text{min}}/2] + ([x_{\text{max}} - x_{\text{min}}]/2)}{\beta} \) |
| +α         | \( X_{\text{max}} \)     |

Note: \( x_{\text{max}} \) and \( x_{\text{min}} \) are the maximum and minimum values of \( X \) respectively, \( \beta \) is 2\(^{n/2} \), \( n \) is the number of variables (rotational speed of shaft (N), submergence depth (h), and propeller angle (α)) and \( n = 3 \).
where $Y$ is the response, $X_i$ stands for the coded values, and $b_i$ stands for the models’ regression coefficients. In the present study, the regression modelling was performed using the Minitab 16 statistical software. Analysis of variance (ANOVA) was carried out to find out significant model terms. All the analyses and inferences were concluded at 5% level of significance.

### 3.4. ANN based modelling

In the present study, a multilayer feed forward neural network model was developed for modelling of operating parameters of a PDA aerator using the MATLAB R2013a package. Its high learning ability and information processing potentiality make it suitable for complex nonlinear modelling without prior knowledge about the input-output relationships, which is difficult to handle with the statistical approach (Pareek et al. 2021). ANNs have better generalizability, less susceptibility to noise and outliers than regression models, and also can handle incomplete data (Luk et al. 2001). The neural network model consisted of three layers of neurons, i.e., the input layer, hidden layer, and output layer. The number of neurons in the input and output layer of the networks was determined by the number of input and output

| Variables                  | Symbol | Coded variable levels | Actual level of variables | Observed | K, $L_a$, h$^{-1}$ | SOTR, kgO$_2$/h | SAE, kgO$_2$/kWh |
|----------------------------|--------|-----------------------|---------------------------|----------|-------------------|-----------------|------------------|
| Rotational speed (N)       | $X_1$  | −1                    | 250                       | 500      | 750               | 1000            | 1250             |
| Submergence depth (h)      | $X_2$  | −0.20                 | 0.30                      | 0.40     | 0.50              | 0.60            |
| Propeller angle ($\alpha$)| $X_3$  | 3                     | 6                         | 9        | 12                | 15              |
parameters, respectively. Thus, the input and output layers consisted of three neurons and one neuron, respectively. The number of neurons in the hidden layer was varied from 1 to 50, and the optimum number of neurons was selected based on the minimum root mean square error (RMSE) value of the network by trial and error method. The optimal value for hidden layer neurons was obtained as 15. Thus, an ANN model configuration of 3–15 – 1 was determined as the optimal network. The topology of the developed ANN model is shown in Figure 3. The individual ANNs were trained using 1000 iterations, the training function used in the hidden layer was logistic sigmoid (‘logsig’) in the hidden layer and linear (‘purlin’) in the output layer, the default training algorithm selected was Levenberg-Marquardt (‘lm’); training and testing phase data had been divided as 70 and 30% of the total dataset, respectively. The experimental data were used for both training and testing.

3.5. Comparison of RSM and ANN models
The goodness of fit and prediction abilities of computed models were evaluated by calculating the coefficient of determination ($R^2$), RMSE, and mean absolute error (MAE). These parameters for both the developed models were compared, and the best fitted model was selected with the higher $R^2$ values and lower MAE and RMSE values. The formulas used for the analyses of the above parameters are given in Equations (8)–(10), respectively. Furthermore, the values predicted by RSM and ANN were plotted against the corresponding experimental values.

$$R^2 = \frac{\sum_{i=1}^{N} (O_i - O)(P_i - P)}{\sqrt{\sum_{i=1}^{N} (O_i - O)^2 \sum_{i=1}^{N} (P_i - P)^2}}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (O_i - P_i)^2}{N}}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |O_i - P_i|$$

4. RESULTS AND DISCUSSION
4.1. RSM modelling
Twenty observed responses were used to compute the models using the least square method. The SAE was correlated with three independent operating parameters (different rotational speed (N), submergence depth (h), and

![Figure 3](http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2021.199/915219/ws2021199.pdf)

Figure 3 | Topology of the developed ANN model for PDA.
propeller angle ($\alpha$) (Table 3), using a second order polynomial, as presented in Equation (11). From the experimental data, a quadratic regression model for different response (SAE) was obtained:

$$SAE = 6.3976 - 0.0034 \times N - 11.3576 \times h - 0.3838 \times \alpha + 1.4072 \times 10^{-6} \times N^2 + 3.6454 \times h^2 + 0.0039 \times \alpha^2 + 0.0024 \times N \times h + 2.0350 \times 10^{-5} \times N \times \alpha + 0.7700 \times h \times \alpha \quad (11)$$

The second order polynomial (Equation (11)) indicates that the model could be well fitted. The coefficient of determination ($R^2$) and p-values were 0.866 and 0.000, respectively. The adjusted value of the coefficient of determination of 0.746 also corroborates the above statement. The model precision is exhibited with a low value of C.V. of 10.17%. The statistical analysis (Table 4) reveals that the linear model terms ($N$, $h$, and $\alpha$) and quadratic model terms ($N^2$, $h^2$, and $\alpha^2$) are significant at 95% confidence level. The interactive model terms ($N \times h$, $N \times \alpha$, and $h \times \alpha$) are not significant ($p > 0.05$).

The ANOVA of the fitted model (Table 5) indicates that the regression is highly significant ($F = 7.21$), while the lack of fit is not significant ($p > 0.05$). Hence, it is inferred that the design model adequately fits the experimental data (Montgomery 1991).

4.2. ANN modelling

The neural network model configuration was found to be the best model configuration. During the training process, the learning rate and momentum factor were selected as 0.9 and 0.1, respectively, and the maximum numbers of epochs was limited to 1000. The model was adaptively trained by trial and error method until the minimum mean squared error (MSE) between the target value and the ANN model predicted value of SAE was achieved. The neural network regression plots between the ANN model predicted and target values for the training set, test set, and the total experimental set are shown in Figure 4. The correlation coefficients ($R$) for training, testing, and all the dataset using the ANN model were 0.9923, 0.9788, and 0.9175, respectively. The different phases (training, testing, and all dataset) indicate a good correlation between the experimental and model predicted SAE values, which implies that the developed ANN model can predict the SAE values with a higher accuracy.

The combination of optimization point of each independent parameter was obtained by using Minitab 16 to maximize SAE and is shown in Table 6. A maximum SAE of 1.711 kg O2/kWh is predicted with $N$, $h$, and $\alpha$ values of 1,000 rpm, 0.25 m, and 12°, respectively. As clean water was used for all the experiments, its density, 1,000 kg/m3 could be taken as constant.

4.3. Performance comparison of RSM and ANN models

The prediction ability of the developed RSM and ANN models were compared using three model performance measures, i.e., $R^2$, RMSE, and MAE. These model performance parameters of developed RSM and ANN models

### Table 4 | Estimated regression coefficients for SAE

| Term   | Coefficient | SE Coefficient | $T$  | $P$ |
|--------|-------------|----------------|------|-----|
| Constant | 1.12616     | 0.04248        | 26.509 | 0.000 |
| $N$    | −0.10300    | 0.05325        | −1.934 | 0.002 |
| $h$    | 0.06075     | 0.05325        | 1.141  | 0.001 |
| $\alpha$ | 0.05900    | 0.05325        | 1.108  | 0.004 |
| $(N)^2$ | 0.35182     | 0.08496        | 4.141  | 0.002 |
| $(h)^2$ | 0.14582     | 0.08496        | 1.716  | 0.007 |
| $(\alpha)^2$ | 0.14082    | 0.08496        | 1.657  | 0.008 |
| $N \times h$ | 0.24200   | 0.15063        | 1.607  | 0.139 |
| $N \times \alpha$ | 0.06100   | 0.15063        | 0.405  | 0.694 |
| $h \times \alpha$ | 0.92400   | 0.15063        | 6.134  | 0.790 |

I.e., at the 95% confidence level of significance, $R^2 = 86.65\%$ and adjusted $R^2 = 74.64\%$. 

Corrected Proof

Water Supply Vol 00 No 0, 8

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Table 5 | Analysis of variance (ANOVA) for SAE

| Source         | DF  | Seq SS   | Adj SS   | Adj MS  | F    | P     |
|----------------|-----|----------|----------|---------|------|-------|
| Regression     | 9   | 0.736603 | 0.736603 | 0.081845| 7.21 | 0.002 |
| Linear         | 3   | 0.071122 | 0.071122 | 0.023707| 2.09 | 0.165 |
| N              | 1   | 0.042436 | 0.042436 | 0.042436| 3.74 | 0.082 |
| h              | 1   | 0.014762 | 0.014762 | 0.014762| 1.30 | 0.281 |
| α              | 1   | 0.013924 | 0.013924 | 0.013924| 1.23 | 0.294 |
| Quadratic      | 3   | 0.207450 | 0.207450 | 0.069150| 6.10 | 0.013 |
| (N)^2          | 1   | 0.154263 | 0.194505 | 0.194505| 17.15| 0.002 |
| (h)^2          | 1   | 0.022027 | 0.033413 | 0.033413| 2.95 | 0.117 |
| (α)^2          | 1   | 0.031161 | 0.031161 | 0.031161| 2.75 | 0.128 |
| Interaction    | 3   | 0.458030 | 0.458030 | 0.152677| 13.46| 0.001 |
| N × h          | 1   | 0.029282 | 0.029282 | 0.029282| 2.58 | 0.139 |
| N × α          | 1   | 0.001861 | 0.001861 | 0.001861| 0.16 | 0.139 |
| h × α          | 1   | 0.426888 | 0.426888 | 0.426888| 37.63| 0.000 |
| Residual Error | 10  | 0.113440 | 0.113440 | 0.113440|      |       |
| Lack-of-Fit    | 5   | 0.097619 | 0.097619 | 0.019524| 6.17 | 0.034 |
| Pure Error     | 5   | 0.015821 | 0.015821 | 0.003164|      |       |
| Total          | 19  | 0.850043 |          |         |      |       |

Figure 4 | Regression plots of the developed ANN model for different phases.
are given in Table 7. These results showed that the ANN models have higher modelling capability and thereby better prediction ability compared to the RSM models for aeration efficiency. Hence, RSM is recommended for modelling of a new process, while ANN is best suited for nonlinear systems that include interactions higher than quadratic.

The RSM and ANN model predicted values and experimental values of SAE are presented in Figure 5. From the figure, it is observed that the ANN model predicted SAE values lie very close to the experimental values of SAE in each run as compared to the RSM model predicted SAE values, which again confirms the excellent approximation capability of the developed ANN model.

4.4. Effects of operating parameters (N, h and α) on SAE

The combined effects of N and h on SAE are shown in Figure 6, N and α on SAE in Figure 7, and h and α on SAE in Figure 8. From Figure 6, it can be observed that the SAE increases gradually with the increase in the rotational speed (N) up to 1,000 rpm as well as with an increase in submergence depth (h) up to 0.50 m. After that, the SAE starts to decline with the further increase in N and h. Similar results were reported by Moulick et al. (2002) and Moulick & Mal (2009) for a paddle wheel aerator. This is due to the fact that at 1,000 rpm, maximum turbulence is created, facilitating the highest oxygen transfer rate, and any higher speed consumes more energy without any increase in oxygen transfer rate resulting in the reduction of SAE. When the submergence depth increases more, the aerator gets loaded, and less water is splashed into the atmosphere. As a result, the increase in water-air interfacial area reduces. In fact, this phenomenon was observed during the experiment. A perusal of the trend of Figure 6 clearly shows that SAE reduces with the increase in depths of submergence above 0.50 m for all

Table 7 | Evaluation criteria used in predicting bonding strength by the RSM and ANN models

| Models | Performance criteria |
|--------|----------------------|
|        | R²      | RMSE   | MAE   |
| RSM    | 0.8665  | 0.3737 | 0.2980|
| ANN    | 0.9175  | 0.1082 | 0.0515|

Figure 5 | Comparison of experimental SAE values with RSM and ANN predicted SAE values.
values of rotational speeds. The obvious reason for this is that with the increased depth of submergence, power requirement increases, but the SOTR reduces, resulting in the reduction of SAE.

From Figure 7, it is seen that SAE increases with the increase in \( \alpha \) up to 12°. However, after a 12° propeller angle, the SAE values decrease up to the tested maximum value of 15°. This is due to the fact that initially although the power consumption increases the SOTR increases comparatively more leading to increased values of SAE. However, after the propeller angle increases to more than 12°, the increase in SOTR is offset by higher increase in the power consumption leading to lowering of SAE. Hence, the optimum value of propeller angle, \( \alpha \) of the propeller diffused aerator can be considered as 12°. This shows that the propeller angle, \( \alpha \) plays a predominant role in oxygen transfer into the water body.

From Figure 8, it is observed that the SAE increases with the increase in \( \alpha \) up to 12°. The SAE increases with the increase in depths of submergence, \( d \) up to 0.5 m, and after that, SAE declines. In fact, this is obvious as with the increased depths of submergence, power requirement increases, whereas the SAE reduces. The maximum SAE value was 1.711 kg O₂/kW h at 1,000 rpm rotational speed, 0.50 m submergence depth, and 12° propeller angle.
5. MODEL VALIDATION

The optimized operating parameters (Table 8) were validated with an additional three sets of experiments to re-check the model. The experimental and predicted values of SAE were 1.711 and 2.020 kgO₂/kWh, respectively. The absolute error was calculated using Equation (12):

\[
\text{Absolute Error (\%)} = \frac{\text{Experimental value} - \text{Predicted value}}{\text{Predicted value}} \times 100
\]  

The absolute error (%) between the experimental and predicted values is only ±15.2%, confirming the adequacy of the model. Hence, the results of validation parameters can be considered satisfactory. Zhang et al. (2020) reported that SAE values of a propeller-aspirator-pump and a diffused-air aeration system were 1.8 and 1.2 kgO₂/kWh, respectively. The results of the present study indicate that the predicted SAE of PDA is higher than the propeller-aspirator-pump and diffused air aeration system.

During a laboratory experiment, clean tap water is needed and temperature should be maintained at 20 °C. Often clean tap water contains chlorine or other impurities. Temperature correction was applied, but the temperature fluctuated slightly during the experimental period. Thus, the conditions needed for testing under standard conditions could not be strictly maintained. Therefore, slight variation between the predicted and experimental values may be attributed to the above factors.

6. CONCLUSION

From the present study, the following conclusions can be drawn:

1. The aeration characteristics of the PDA aerator depend on operating and geometric parameters, rotational speed of aerator (N), depth of submergence (h) and propeller angle (α).
2. To achieve the maximum standard aeration efficiency, N, h and α should be 1,000 rpm, 0.50 m, and 12° respectively.
3. Under the optimum operating conditions, the maximum SAE was found to be 1.711 kg O₂/kWh.
4. Performance comparison of RSM and ANN models shows that ANN is a better and more effective tool than RSM due to its higher R² and lower RMSE values.
5. The cross-validation results show that the best approximation of optimal values of input parameters for maximizing the SAE is possible with a maximum deviation (absolute error) of ±15.2% between the model predicted and experimental values.

6. The developed ANN model is an effective tool for predicting the standard aeration efficiency of the PDA aerator and may also be applied to determine the optimal operating parameters of other aerators.

The study had a number of limitations:

1. The SAE was determined from laboratory experiments conducted by following standard conditions suggested by ASCE (2007).

2. The experimental results could not be verified under actual field conditions due to practical limitations.

3. The coefficients α (\(k_{La20}\) pond water/\(k_{La20}\) of tap water) and β (DO saturation concentration of pond water/DO saturation concentration of clean water) should be considered, while using the results for actual pond water. For actual field applications, the optimized operating parameters can be used to scale up the PDA aeration system.

**DATA AVAILABILITY STATEMENT**

All relevant data are included in the paper or its Supplementary Information.

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