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Modeling of dissolved oxygen parameter and optimization using RSM and ANN for paint industry effluent in semi batch fermenter

P. Aravind[a,*], J. Sumathi[b]

[a]*Department of Instrumentation and Control Engineering, Saranathan College of Engineering, Tiruchirappalli, India, email: aravindpvenky@gmail.com*
[b]*The Institution of Engineers (India) [IEI], Thanjavur Zone, Tamil Nadu India, email: suma22mathi@gmail.com*

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ABSTRACT

Effluents from industries such as textile, distillery, bone wash, paper, and paint pose serious environmental hazards and lead to health problems for human beings. The purpose of this study is to analyze the dissolved oxygen parameter in such industrial effluent. The dissolved oxygen was monitored and recorded for ten concentrations and three different speeds with time till DO reached saturation in paint industrial effluent. Based on the data generated from 270 experimental results, the optimization techniques response surface method (RSM) and artificial neural network (ANN) are proposed to find the optimized operating parameters with 17 experimental runs using three inputs time, speed, and feed concentration. In RSM analysis, with a single objective function, a second-order quadratic has been represented with a higher degree of fitting which produced R^2 = 99.85% and R^2_{adj} = 99.65%. From ANN analysis, with the support of optimization tool ANN produced R^2 = 91.45%, R^2_{adj} = 93.82%. From the analysis, it is evident that RSM performed better than ANN. The error percentage is 0.59% which validates the predicted model from the predicted and confirmatory experimental results. From this experimental study, we can conclude that RSM-based results give superior results compared to ANN results.

Keywords: Paint industry effluent; Semi batch fermenter; Box–Behnken design; Artificial neural network; Dissolved oxygen

1. Introduction

Industry effluent contains a large variety of dyes, chemicals as a raw materials that pose a great health hazard and if these are discharged without proper treatment, it disturbs the biological activities and equilibrium of the aquatic ecosystem. Furthermore, if these raw materials coalesce with dissolved oxygen in water makes them carcinogenic, toxic and mutagenic, it may lead to allergies and even make the health worst of living beings. Therefore, it is crucial that effluents from the industries are must be treated in an adequate way before discharging. Many researchers have done a research on waste water treatment and few of their research works are highlighted below to know the importance of treatment of waste water from industries. Esteves et al. [1] evaluated online monitoring of biological wastewater plants treating simulated textile effluent for use in the control strategy.

Vives et al. [2] conducted over a laboratory-scale sequencing batch reactor system using data acquisition and control software. Al-Kdasi et al. [3] discussed an overview of basis and treatment efficiency for different advanced oxidation processes are considered and presented according to their specific features.

Hanafy and Elbary [4] work is concerned with the treatment of wastewater effluent of paint industry and treatability studies have been conducted. It was implemented using a sequential batch reactor as a biological treatment system.

* Corresponding author.

Baskar et al. [5] utilized the textile industry effluent as a partial replacement for clay in the conventional brick manufacturing process. Yifeng [6] developed a sensor for the detection of dissolved oxygen using a graphite paste with high accuracy, excellent stability, and fast speed. Lina et al. [7] used sequence batch reactor technology to analyze the biological treat wastewater discharge from the textile industry.

Tewari et al. [8] conducted a survey of 36 distilleries and highlighted the status of wastewater generation in Indian distilleries. Research and development in wastewater treatment and disposal is enlighted. Work was undertaken by Sandip et al. [9] uses RSM optimization for removal of hydrochloride from the simulated pharmaceutical waste.

An investigation by Bahadr Körbahti et al. [10] was done in the presence of NaCl electrolyte with carbon electrodes on the electrochemical oxidation of water-based paint wastewater treatment. As indicated by these results, the electrochemical strategy could be a solid option in contrast to regular physicochemical strategies for the treatment of water-based paint squander water.

Ramesh Babu et al. [11] discussed methods of oxidation biotreatment in the petrochemical and membrane process.

Fersi and Dhahbi [12] showed using the ultrafiltration process as a pretreatment for the nano-treatment process improved the textile effluent efficiency treatment by increasing the membrane run-time.

Sowmeyan and Swaminathan [13] recommended physiochemical and biological treatment methods and treating effluent from molasses from inverse anaerobic fluidization is a better choice. Satyavali and Balakrishnan [14] explored distinctive interactions covering natural and physiochemical strategies to treat the gushing and diminish the remaining natural burden and shading in the molasses-based refinery squander water. Saravanan et al. [15] contemplated the treatment of refinery effluent utilizing an oxygen-consuming reactor. Sewage muck was utilized as seed culture to treat the effluent and worked under various fixations.

Trial impacts of untreated refinery emanating, released from refinery unit, and post-treatment gushing from the power source of anaerobic treatment plant were concentrated on mung bean by Kannan and Upreti [16]. Samarghandi et al. [17] done a research on process for 2,4-D herbicide removal from aqueous solutions using stainless steel 316 and graphite anodes using RSM.

Badkar et al. [18] analyze the impacts of process factors of laser-hardened pure titanium on heat input and tensile strength using the RSM and ANN model. Thoai et al. [19] applied RSM and ANN for biodiesel production via base-catalyzed transesterification. Obtained models are compared to optimize the methyl esters production process from edible oils. Onu et al. [20] compared four methods are RSM, ANN, and ANFIS, and the mechanistic method of modeling in eriochrome black-T dye adsorption using modified clay. Heidari et al. [21] have analysed the effect of operating parameters, intermediate identification, degradation pathway, and optimization using RSM by electro-Fenton process.

Sumathi et al. [22] used RSM and ANN optimization methods to find the optimal model parameters for dissolved oxygen process parameters using paper mill effluent in a semi-batch fermenter.

Saravani and Arulmozhi [23] uses RSM to address the impact of different process factors of o-cresol onto Bacillus cereus and cetyl ammonium bromide on the biosorption foam separation. Almasi et al. [24] analysed and studied effects on removal of carbon and phenol from the petroleum industry wastewater. Samarghandi et al. [25] have found optimal operational parameters to improve the biodegradability of textile effluent. Samarghandi et al. [26] have a analyse on degradation and it is investigated in a three-dimensional electrochemical reactor. Dargahi et al. [27] uses the application of a fluidized three-dimensional electrochemical reactor for process optimization and degradation pathway. Afshin et al. [28] uses Box–Behnken design for optimizing parameters of hexavalent chromium removal from aqueous solutions. Hasani et al. [29] have improved the efficiency of electrochemical, Fenton, and electro-Fenton processes using anodes to remove oxytetracycline antibiotic from aquatic environments. Dargahi et al. [30] use RSM to find the optimal influencing factors for degradation of diazinon insecticide from aqueous solutions in an advanced oxidation processes.

In effluent treatment, dissolved oxygen (DO) is an important process variable in these plants. DO refer to the quantity of free oxygen dissolved in a unit volume of water. DO is expressed in mgm per liter or in ppm. The quantity of DO for example in the range of 4–5 mg/L affects the health of fishes and below 2 mg/L can be lethal. A very high value of DO indicates that the oxygen intake by microorganisms is a low and subsequent breakdown of nutrient sources. The amount of free or DO present in effluent becomes too low, the aerobic bacteria will expire and putrefaction occurs and when the DO level is too elevated, energy will be devastated in the aeration of the effluent. In industrial applications, the DO level should be little to forestall erosion and heater increase assemble which restrains heat move. In developing countries in many places, these treatment plants are being handled by people not so well conversant about the seriousness of the problem. Even though DO is measured as ppm or mg/L, measure the partial amount of oxygen in the water. Dissolved oxygen level is reliant on both salinity and temperature. Most of all biotechnological measures are of an oxygen-consuming kind. A microorganism or cell reacts to the fluid stage oxygen fixation in controlling its general digestion. Subsequently, information on the DO fixation and the appropriate control during the interaction is of incredible significance. In this work, dissolved oxygen is considered as a process variable for experimental analysis in paint industrial effluent. The graphical abstract of the work (experimental setup) is shown in Fig. 1.

2. Materials and method

2.1. Experimental setup and procedure

The present study was experimental and was conducted in a laboratory-scale pilot. In this study, industrial waste from paint industry was considered for analysing the variation of dissolved oxygen parameter. The experimental setup for the batch process was fabricated with a speed adjustable agitator in a semi-batch reactor is shown in Fig. 1 and the line diagram [22] is shown in Fig. 2.

It consists of a lark hygiene fermenter, rotameter, effluent storage, stirrer, control valve, dissolved oxygen probe (DO), and personal computer. The components with the specification are given in Table 1. The 1.5 L semi-batch reactor has provisions to regulate the air flow, stirrer speed, and temperature. The effect of time, agitation speed, and feed concentration on dissolved oxygen for paint industry effluent were studied. The effluent is diluted with water from 10% to 100% in steps of 10%. One litre of the effluent was charged into the reactor. At the moment of time t = 0, clean air was abruptly supplied through a pre-calibrated rotameter at a flowrate of 1 lpm into the fermenter. Dissolved oxygen (DO) using a DO probe was observed in a personal computer. Three speeds 135, 145 and 155 rpm were chosen to study the effect of the speed on the variation of DO with time. The experiment was carried out at room temperature. The experimental results with dilution in steps of 10% from 10% effluent to 100% effluent for three different speeds of 135, 145, and 155 were obtained and consolidated. Fig. 3a and b show the experimental and calculated readings for speed 155 rpm from 100% and 10% paint industry effluent concentration.

3. Optimization using RSM and ANN

In the Industrial arena, the above experimental runs in higher numbers (270 experimental runs per effluent) lead to time consumption and higher cost of the process to identify optimal process parameters [31] and to design the controller. Therefore in order to reduce the number of experimental runs and time consumption, [32] response surface methodology (RSM) based BBD [33] which reduces the 270 experimental runs into 17 experiments per effluent was deployed with the same influential parameters and

Table 1
Fermenter components and specification

Fermenter	Type: Lark Hygene Fermenter, Manufacturer: India
Fermenter container	Total volume: 3 L; H × D: 250 mm × 150 mm
Aeration	Air outlet with 0.2 microfilter; Air sparger – L-type with micropores
Mixing assembly	Viton V-rings; 2 Smooth bearings; 2-Impeller with 6 blades each; 3 baffles
Agitation	Stirrer PMDC motor; Accuracy 1 rpm; Speed range: 20–1,000 rpm
DO control	Accuracy 0.1 mg/L or +/–1%; Operating range 0–100%
Rotameter	Range: 0.5–5 L/min

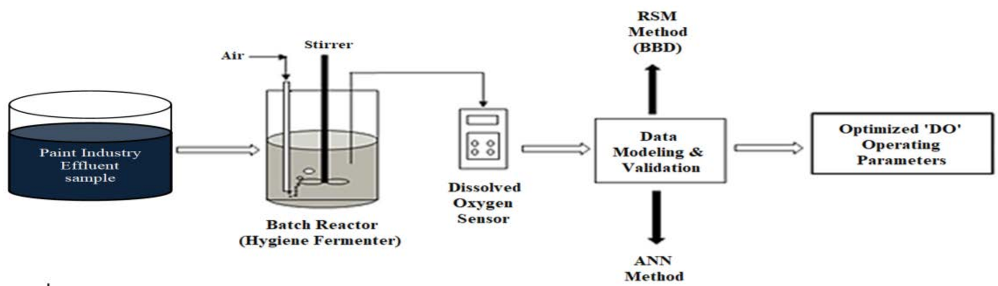

Fig. 1. Experimental setup for process model.

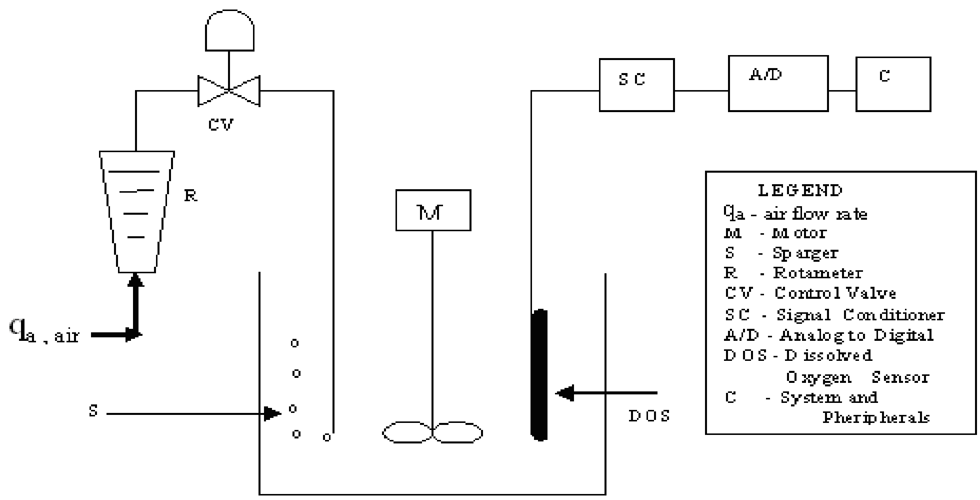

Fig. 2. Line diagram of experimental setup.

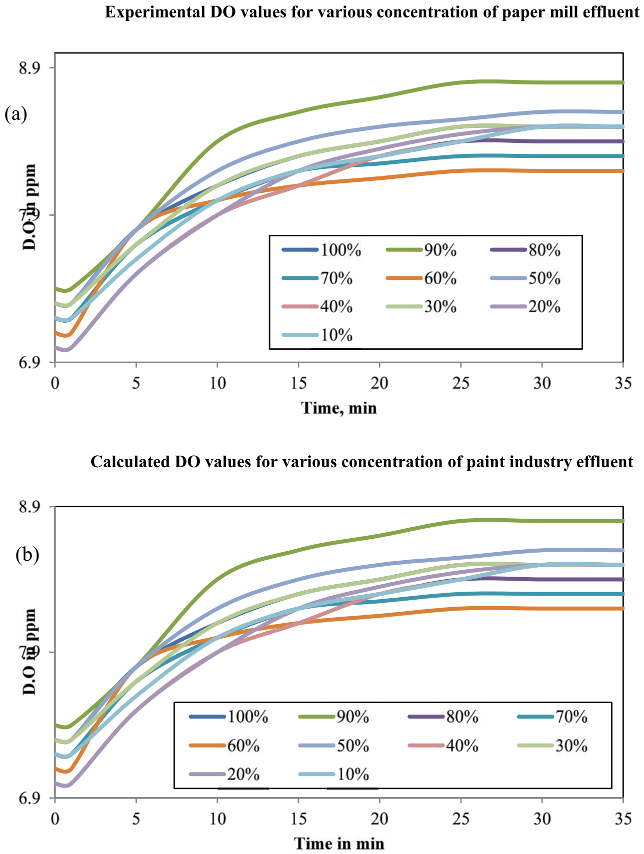

Fig. 3. Experimental and calculated data for 155 rpm for 100% and 10% concentration.

desired levels. Added to this fact, it also helps in identifying the significance of the interaction of input parameters which holds the advantage over the selective levels of particular process parameters. ANN has been used to develop a model using data obtained from the experimental results of paint industry effluent. From the optimal model parameters of DO obtained from RSM, it was compared with ANN.

3.1. Experimental design employing BBD with RSM

RSM is the best suited experiential optimization practice to evaluate the association between input parameters and experimental outputs [34–36]. RSM method is adopted process of Black Box Design (BBD) and Central Composite Designs (CCD) [37–40]. Without disturbing the optimization accuracy BBD specifically reduce the number of experimental sets judged against the conventional factorial design (CFD) method [41]. The three factors used as independent variables are time, speed, and concentration. These factors were varied at three different levels (–1, 0, +1) from minimum to maximum level, as shown in Table 2. The following Eqs. (1) and (2) describe the relationship between the uncoded and coded variables.

$$a_1 = \frac{\left(A_1 - 15\right)}{15} \tag{1}$$

Table 2
Three factors levels in terms of coded and uncoded symbols

Experimental variable	Variables		Levels		
	Coded	Uncoded	–1	0	1
Time (min)	a_1	A	0	15	30
Speed (rpm)	a_2	B	135	145	155
Concentration (%)	a_3	C	10	50	90

$$a_2 = \frac{\left(A_2 - 145\right)}{10} \tag{2}$$

$$a_3 = \frac{\left(A_3 - 50\right)}{40} \tag{3}$$

where A_1, A_2 and A_3 are the uncoded variables with own units and a_1, a_2 and a_3 are the coded variables respectively. To formulate the factors of coded variables dimensionless. The impacts of the three variables on the DO is approximated using quadratic model shown in Eq. (4).

$$y = b_0 + \sum_{i=1}^{n} b_i X_i + \sum_{i=1}^{n} b_{ii} X_{ii}^2 + \sum_{i<j} \sum_{j}^{n} b_{ij} X_i X_j \tag{4}$$

Let y is the predicted response (dissolved oxygen in ppm), b_0, b_i, b_{ii}, b_{ij} are offset term, linear effect, square effect, interactive effect respectively and X_i, X_j is the variables that are independent as well as coded [23].

Design–Expert software version 11.0.1 is used for the analysis of variance, experimental design, optimization of the process parameters and regression analysis [42]. The coefficient of regression (R^2) and p-value of the analysis of variance (ANOVA) will be obtained and used to resolve the suitability of the model.

3.2. ANN modeling

In ANN, artificial neurons use machine learning techniques to obtain the results. Added to it [22] discussed that the ANN model can be estimated using the same experimental data set used in RSM. Minimization of the objective function is done using the Backpropagation technique. For training, the network Levenberg–Marquardt algorithm is used, and mean square error (MSE) is used for performance measures. The Levenberg–Marquardt algorithm works with the Jacobian matrix and gradient vector. Its design works with sum of the squared errors (loss function).

Matlab (R2016b) is used for ANN modeling. 17 experimental runs have been proposed by considering all probable permutations of factors and also considering values given in Table 2. The 3–10–1 ANN architecture used as shown in Fig. 4 is proposed. The ratio 70:15:15 of input data taken for training, validation, and testing respectively. The parameters time, speed, and concentration are used to train the ANN. The mean square error (MSE) is used for evaluating the performance of the model. The predicted R^2 is 91.45% and R^2_{adj} is 93.82%.

4. Results and discussion

4.1. Model fitting and analysis of variance

Box–Behnken design used for analysis and statistical summary of short of fits for each model is found employing Design–Expert V8 software [43] is shown in Table 3. Table 4 shows the experimental and predicted DO values for paint industry effluent under different concentrations. With the better R^2 and R^2_{adj} a second-order quadratic model has been suggested and the obtained values are R^2 = 91.45%, R^2_{adj} = 93.82%.

Table 5 states that in reference to given settings, to determine the DO points, quadratic and intuitive impact among the picked their boundaries contributed in own particular manner. Thus, the quadratic model was distinguished.

4.2. Model fitting, modification and analysis of variance

The generated result fits the selected quadratic based on the exploration by the model [44]. The connection between the three input parameters *A*, *B*, *C* are time, speed, and feed concentration respectively, and dissolved oxygen is given in Eq. (5).

$$\text{Dissolved oxygen} = +9.00 + 1.05A - 0.14B - 2.06C + 0.075AB - 0.33AC + 0.35BC - 0.85A^2 - 0.48B^2 - 0.62C^2 \quad (5)$$

The proportion, the disclosed variety to the all-out variety is characterized as the coefficient of determination (R^2); a assess the level of fit. At the point when a model capitulates an R^2 of 0.9, it very well may be considered as a decent model [22]. This implies that the response model utilized in this examination expresses in a well way the process, at 95% certainty point, keeping R^2 = 99.85% and R^2_{adj} = 99.65%. Furthermore, the value of F = 503.67 (F) with the probability value as low as $p < 0.001$ and is genuinely significant for consideration.

The significant model and results for paint industry effluent *A*, *B*, *C*, *AC*, *BC*, A^2, B^2, C^2 obtained from ANOVA is given in Table 5. Parameters time, speed, and feed concentration are the coefficients for the quadratic terms are point to be very significant, which surmises that these parameters comprise extremely large impacts on the dissolved. This result likewise tracked down that the interaction impact of time and speed is not significant. Despite the fact that time and speed aren't critical, the speed of mixing doesn't influence the time for saturation.

Minimizing the oxidation time to accomplish saturation as far as DO helps in diminishing the force needed for running the compressor. Mixing action doesn't influence as seen in the light of the fact that the rising of the air itself makes turbulence and better blending. After assessing the worth of the boundaries, the model is able to be made do by taking out the extremely less noteworthy terms. The final model is given in Eq. (6).

$$\text{Dissolved oxygen} = -82.14 + 0.13A + 1.31B - 0.13C + 5.0AB - 5.41AC + 8.75BC - 3.77A^2 - 4.75B^2 - 3.90C^2 \quad (6)$$

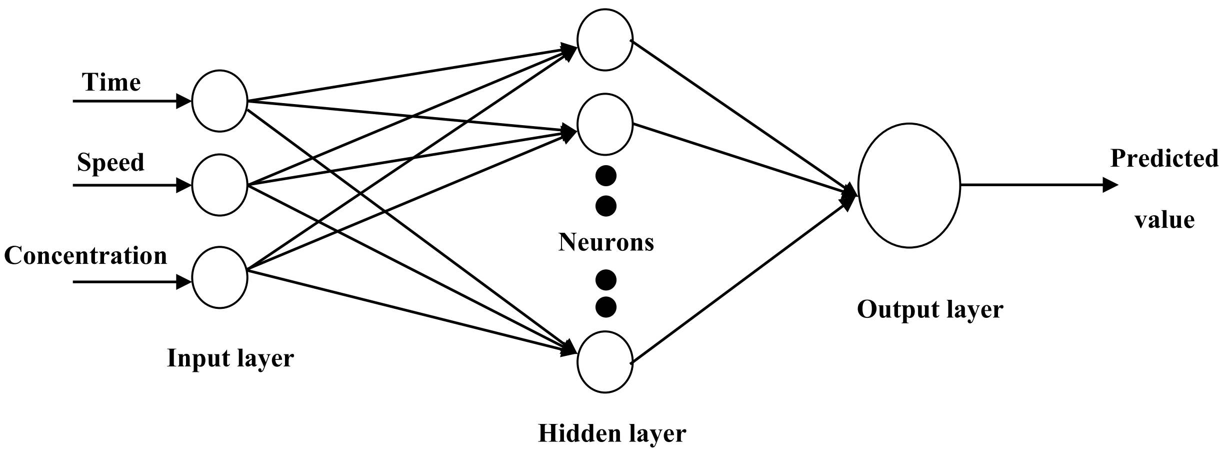

Fig. 4. Neural network architecture.

Table 3
Statistical summary

Basis	Degree of freedom	Total of squares	Mean square	F-value	p-value Prob. > F	Suggestion
2F1 vs. linear	3	0.93	0.31	0.49	0.7493	–
Linear vs. mean	3	43.00	14.33	25.66	<0.0001	–
Cubic vs. quadratic	3	0.078	0.026	6.366E+007	<0.0001	Aliased
Quadratic vs. 2F1	3	6.25	2.08	188.16	<0.0001	Suggested

Table 4
Experimental and predicted data

Run	Coded variables			Real variables			Dissolved oxygen (ppm)	
	a_1 Time (min)	a_2 Speed (rpm)	a_3 Concentration (%)	*A* Time (min)	*B* Speed (rpm)	*C* Concentration (%)	Experimental	Predicted
1	0	–1	1	15	135	90	6	5.96
2	1	1	0	15	145	50	8.1	8.1
3	–1	0	–1	0	155	50	9.3	9.29
4	0	1	1	30	135	50	9	8.97
5	–1	1	0	0	145	10	9	7.97
6	–1	0	1	15	135	90	8.8	8.7
7	–1	–1	0	15	145	50	6.3	6.19
8	0	0	0	15	135	10	10.5	10.37
9	0	–1	–1	15	145	50	10.9	10.8
10	0	0	0	30	145	90	9	8.97
11	0	1	–1	30	155	50	5.5	5.44
12	1	0	1	0	135	50	9	8.97
13	0	0	0	15	155	10	8.8	8.64
14	0	0	0	15	145	50	9.6	9.58
15	1	0	–1	30	145	10	6.4	6.4
16	1	–1	0	15	145	50	9	8.97
17	0	0	0	0	145	90	6.3	6.23

Table 5
Analysis of variance results for acquired model

Basis	Total of squares	Degree of freedom	Mean square	*F*-model value	*p*-value Prob. > *F*	Characteristics
Model	50.19	9	5.58	503.67	<0.0001	Significant
A – Time	8.82	1	8.82	796.65	<0.0001	Most significant
B – Speed	0.15	1	0.15	13.66	0.0077	Significant
C – Feed concentration	34.03	1	34.03	3,073.79	<0.0001	Most significant
AB	0.022	1	0.022	2.03	0.1970	Not significant
AC	0.42	1	0.42	38.16	0.0005	Significant
BC	0.49	1	0.49	44.26	0.0003	Significant
A^2	3.04	1	3.04	274.77	<0.0001	Most significant
B^2	0.95	1	0.95	85.81	<0.0001	Most significant
C^2	1.64	1	1.64	148.56	<0.0001	Most significant
Residual	0.077	7	0.011	–	–	–
Lack of fit	0.077	3	0.026	–	–	–
Pure error	0.00	4	0.00	–	–	–
Cor. total	50.26	16	–	–	–	–

The regression model was additionally assessed using analysis of variance (ANOVA), and the outcomes are displayed in Table 5. The low likelihood value shows that the model is exceptionally huge. The decency of attack of the model was additionally taken a look at utilizing the assurance coefficient (R^2); the values are. Moreover the value of R^2 additionally demonstrates that the model can clarify 99.85% of the all-out variety of the productivity to the operating parameters. To envisage the connection between the operating factors and efficiency, linear plots and contour maps were generated and shown using Design–Expert (version 7.0) based on the regression model.

4.3. Model accuracy check for RSM

To get a plentiful model, a precision check is unavoidable; by looking at the predicted and experimental dissolved oxygen the exactness of the model was verified. Fig. 5 presents the linear relationship among the experimental and predicted dissolved oxygen. Thusly, the remaining be able to be verified to decide the level that the model fulfills the suspicions of analysis of variance, and the internally studentized residuals be capable to gauge the standard deviations (SD) isolating the predicted and experimental values. Fig. 6 illustrates the association between the internally studentized residuals and typical probability (%).

4.4. Optimization by RSM

To identify the optimal model parameters response surface method was used in Design–Expert software [45]. Time, speed, and feed concentration with respective DO were considered for analysis, and the relationship between these parameters is given in Fig. 7a–f. Each plot illustrates the impacts of any two factors inside their thought about ranges, with the 3rd factor set to the degree of nothing. The inclination of each factor in impacting the dissolved oxygen can be envisioned better in the reaction surface.

Prominent interaction among two variables is encountered in an elliptical contour plot. From the response surface and contour plot, it is clear, that the relations impacts of feed concentration and time is more significant. Fig. 7a and b demonstrate speed has a slight impact on DO saturation whereas Fig. 7c and d shows that dissolved oxygen esteems adjust under feed concentration and time for a specific speed.

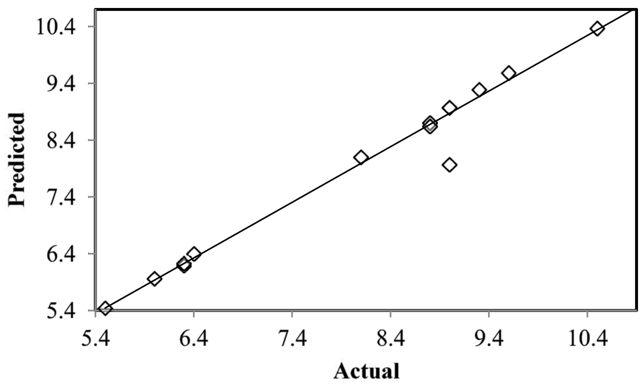

Fig. 5. Actual vs. predicted data.

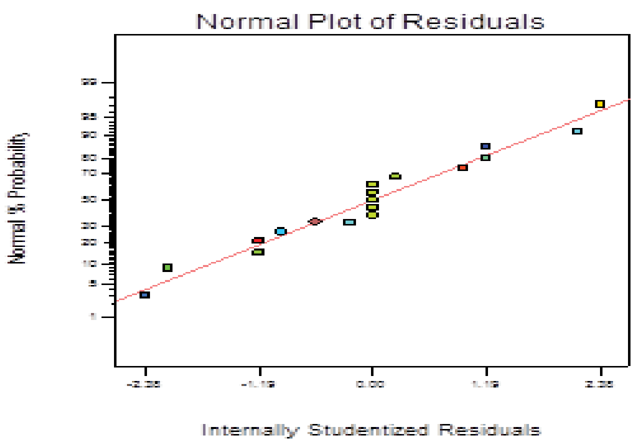

Fig. 6. Normal plot of residuals showing the relationship between normal probability (%) and internally studentized residuals.

Fig. 7e and f show indeed that speed has a small impact on DO variation with feed concentration and time. As seen from these plots, the least considerable factor is speed when contrasted with feed concentration and time. Time assumes a larger part in effluent saturation. This impact proposes that the speed of mixing doesn't influence the time for saturation.

4.5. Modelling by ANN

The obtained experimental results using paint industrial effluent were used to develop an artificial neural network-based mathematical model. Regression plots obtained using ANN by training validation, testing, and overall predicted model are presented in Fig. 8. Table 6 states the predicted response for dissolved oxygen by ANN. It tends to be seen that the overall R^2 is 91.45% and R^2_{adj} is 93.82% predicted by ANN, the predicted model is recommended for modeling and optimizing for DO. R^2 values of training and analysis as well propose that the artificial neural network model be adequately trained as well as it grasps superior in the calculation of new value. Predicted models of both ANN and RSM are near to the experimental results and the R^2 value of RSM prediction compare to ANN prediction was a higher degree of fitness.

4.6. Condition optimization and confirmation tests

In reference to obtained results, the predicted input factors using RSM were chosen for the confirmatory experiment because of their fitness and is presented in Table 7. The minimized DO of 8.84 was calculated at a time of 15 min, feed concentration of 50%, and speed of 144 rpm was found using Design–Expert Software.

In RSM optimization, confirmatory trials were managed to keep the condition best possible to confirm the predicted end result. The analysis concluded that feed concentrations and time exclusively contributed towards the DO minimization. The connection impact of time is transcendently significant towards the different effluent concentrations. The minimum value of DO shows the good agreement between the predicted and experimental outcomes which approves the legitimacy of the model with the error of 0.59%. Table 8 clearly shows to facilitating RSM is the more remarkable and compelling tool for optimization.

In Design Expert Software RSM was used to obtain the optimal model parameters of DO process. By assuming time, speed, and feed concentration as input functions aligned with the contribution of DO. The predicted optimal conditions by RSM for dissolved oxygen were 8.84 ppm at time 15 min, speed 145 rpm, and 50% feed concentration. The RSM result was very near to the confirmatory experimental value of 8.89 ppm.

The results were similar to study carried out by [22], which indicated that the treatment of containing wastewater from paper mill industry RSM gives the superior results with R^2 of 99.85%. The results of the conducted studies are consistent with the present study. Regarding the parameters, it can be said that increasing each of these parameters directly has an effect on the efficiency.

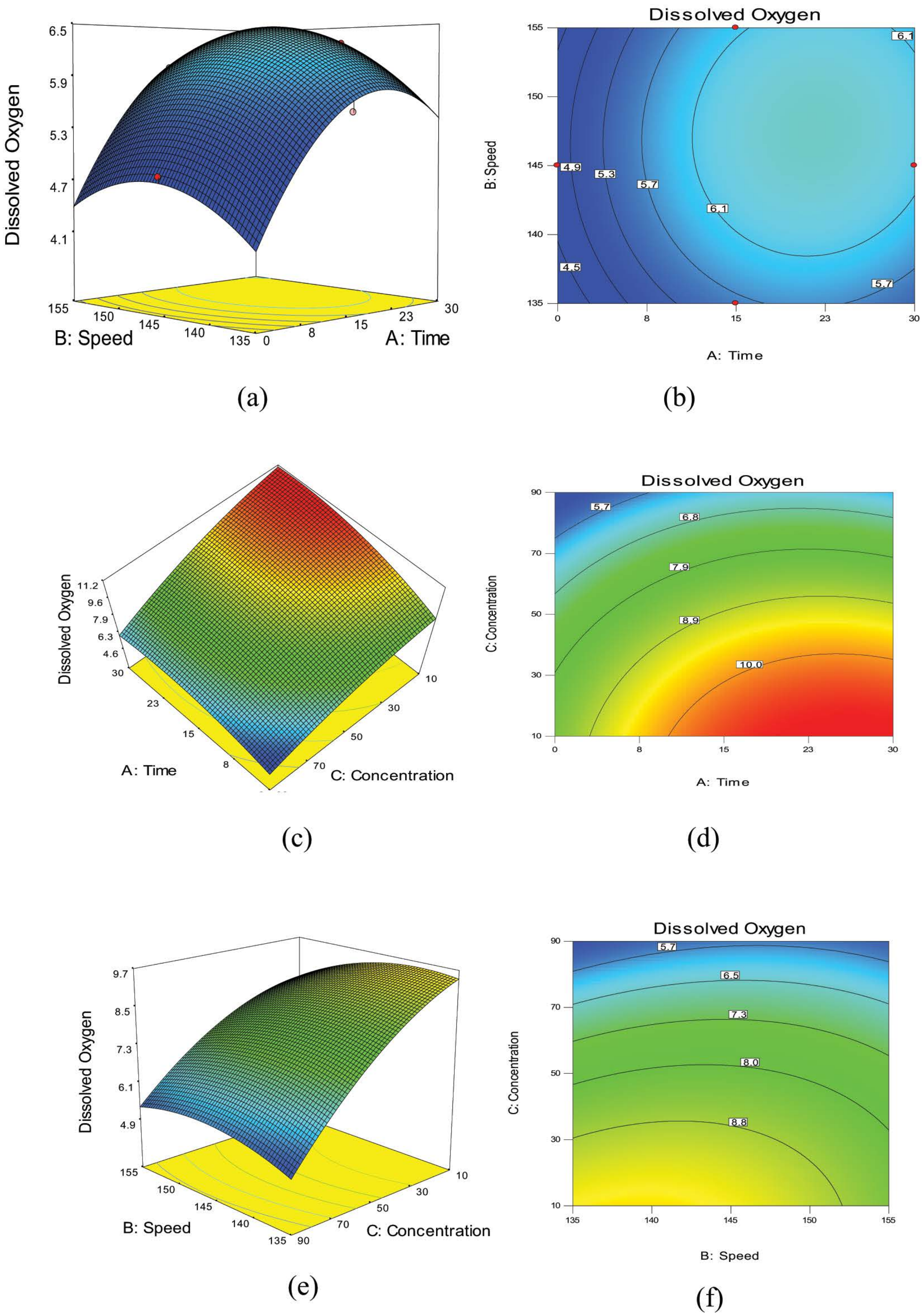

Fig. 7. Surface and contour plots showing the interactive effects of dissolved oxygen with time, speed and concentration.

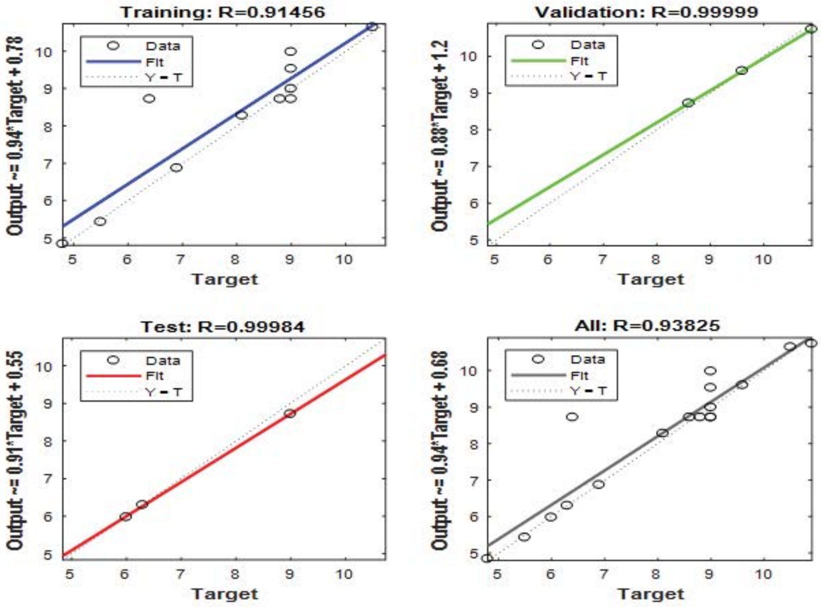

Fig. 8. Regression plots of ANN model for paint industry effluent.

Table 6
Predicted response for dissolved oxygen by ANN for paint industry

A Time (min)	*B* Speed (rpm)	*C* Concentration (%)	Experimental	Predicted
15	155	90	6.0	5.87
0	145	10	8.1	7.9
30	155	50	8.6	8.4
15	145	50	9.0	9.8
15	145	50	9.0	9.8
30	135	50	8.8	8.6
30	145	90	6.3	6.1
15	135	10	10.5	10.3
30	145	10	10.9	10.7
15	145	50	9.0	9.0
15	135	90	5.5	5.3
15	145	50	9.0	8.8
0	135	50	6.9	6.7
15	155	10	9.6	9.7
0	155	50	6.4	6.2
15	145	50	9.0	8.8
0	145	90	4.8	4.6

Table 7
Predicted and confirmatory experimental results for RSM

Result	Time (min)	Speed (rpm)	Concentration (%)	DO (ppm)
Predicted result using RSM	15	145	50	8.84
Confirmatory experimental result	15	145	50	8.25
Error percentage				0.59%

Table 8
Predictive capacity of RSM and ANN

Parameters	RSM	ANN
RMSE	8.08	01.32
R^2	99.85	73.55
R^2_{adj}	99.65	75.58

5. Conclusion

The research work analysis was carried out in a batch study and it evaluates precisely the effect of effluent and water proportion and stability on DO. The optimization techniques RSM and ANN are proposed to find the optimized operating parameters with 17 experimental runs using three inputs time, speed, and feed concentration against DO of the paint industrial effluent. In RSM analysis, with a single objective function, a second-order quadratic was signified with a higher degree of fitting with R^2 = 99.85% and R^2_{adj} = 99.65%. From ANN analysis, using optimization tool ANN produced R^2 = 91.45%, R^2_{adj} = 93.82%. From the analysis, it is evident that RSM performed better than ANN. The error percentage is 0.59% which validates the predicted model from the predicted and confirmatory experimental results.

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