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Modeling oxygen and organic matter concentration in the intensive rainbow trout (*Oncorhynchus mykiss*) rearing system

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Abstract Dissolved oxygen (DO) as one of the most fundamental parameters of water quality plays a vital role in aquatic life. This study was conducted to predict DO, biological oxygen demand (BOD), and chemical oxygen demand (COD) in an intensive rainbow trout rearing system with different biomass (B). The multilayer perceptron (MLP) and the radial basis function (RBF) neural networks were employed for evaluating the impacts of food parameters (crude protein (CP), consumed feed (CF)), fish parameters (different values of B, and weight gain (WG)), and water quality parameters including temperature (T) and flow rate (Q) on variation of DO, BOD, and COD concentrations. This study's results showed that although both MLP and RBF neural networks are capable to estimate DO, BOD, and COD concentrations, RBF neural network showed better performance compared to MLP neural network. The results of sensitivity analysis indicated that the parameter CF has the highest effect on DO concentration estimation. Independent variables CF, CP, WG, and B showed the highest to the lowest rank of impacts on BOD estimation, respectively. The results also illustrated a decreasing trend of the effects on the estimation error of COD changes simulation by all independent variables, including B, T, WG, CF, CP, and Q, respectively. RBF neural network based on better stability and generalization ability with average root mean square error (RMSE) and mean absolute percentage error (MAPE) values of less than 0.12 and 3% was superior to MLP in DO, BOD, and COD concentration prediction. Moreover, CF was identified as the most effective factor in estima12tion process. Based on the present study results, there are direct relationships between DO, BOD, and COD concentrations and water quality parameters, fish parameters, and food parameters. Food parameters relative to fish and water quality parameters imposed the greatest effects. Improvement in feeding process such as application of intelligence feeding methods and change in fish diet and feeding time can considerably reduce losses in production system.

Keywords Artificial neural networks · Different biomass · Fish culture · Prediction

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Introduction

Rainbow trout (*O. mykiss*) is one of the most important cold water fish species in the world. Production of rainbow trout has reached to more than 126,515 t by 2014. Major producing countries include Norway, France, Italy, Spain, Denmark, USA, Germany, Iran, and the UK (FAO 2014). Cold water fishes are highly sensitive to water quality factors (Nafisi Behbaadi 2006). Proper control of water quality keeps the concentration of water quality

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parameters in the optimal range, increases the growth rate and feed utilization efficiency, and reduces the incidence of diseases of cultured species at commercial scale (dos Santos Simões et al. 2008; Stigebrandt et al. 2004). Water quality can be affected by many factors, including concentration of dissolved oxygen (DO), pH, electrical conductivity (EC), temperature (T), biological oxygen demand (BOD), chemical oxygen demand (COD), chloride, total phosphate, nitrite, nitrate, ammonia, salinity, total suspended solids (TSS), and fecal coliform (Mulholland et al. 2005). Measuring all physical, chemical, and biological factors is difficult (Ma et al. 2014), although each environmental (physicochemical) factor plays an important role in changing water quality. Total and mutual relationships between factors ultimately determine how well the fish grow and stay healthy (Anyadike and Ndulue 2011).

DO concentration is the most important parameter of water quality (Mohan and Kumar 2016) and affect the health of aquatics (Ranković et al. 2010). Various aquatic systems such as reservoirs and ponds control water quality (Singh et al. 2009) by use of DO concentration evaluation. The concentration of DO generally depends on parameters such as temperature, altitude above sea level, and salinity. When fish culture is carried out in freshwater, the effect of salinity on the reduction of DO can be neglected (Nafisi Behbaadi 2006). On the other hand, the amount of DO depends on the stocking density, food consumption, and flow rate variation (Wu et al. 2015; Liu et al. 2016; Zhou et al. 2018). Since DO concentration also reflects the balance between oxygen-producing and oxygen-consuming processes (Ahmed 2017), it can be argued that DO with BOD and COD is closely related. BOD and COD concentration varied by different parameters such as suspended solids (SS), pH, un-ionized ammonia (NH3-N), temperature (T), and flow rate (Q) (Ay and Kisi 2014).

So far, many models have been developed to predict important parameters of water quality in the aquaculture industry and other water resources. In a study, effect of two culture densities (15 and 40 kg M^{-3}) and two dietary energy levels (22 and 27 MJ kg^{-1} respectively) during 75 days on growth performance and metabolic and oxidative status of rainbow trout (*O. mykiss*) was studied. They used ANOVA method for evaluation of the effects of culture density and dietary energy level. Their study results indicated that a combination of high culture density and a high level of dietary energy (27 MJ kg^{-1} in diet) showed a negative impact on the physiology and the welfare of the farmed fish (Suárez et al., 2015). In another study, effect of aeration and oxygenation on growth and survival of rainbow trout in a commercial serial-pass, flow-through raceway system was evaluated. This system is characterized by reduced water quality as water passes from upper to lower raceways. They stocked rainbow trout (126 ± 9.3 g mean weight) into tanks receiving either first use (source spring), third use (after two raceway passes), or fifth use water (after four raceway passes) with and without supplemental air or oxygen. Average DO concentration was highest in first use (92.0% saturation) followed by third use (79.4%) and fifth use (52.1%) water. In fifth use water, aeration (68.4%) or oxygenation (71.7%) raised the DO levels similar to third use water. Their study results indicated that growth performance and survival were significantly lower for trout in fifth use compared to first and third use water. Third use water showed higher survival relative to fifth use with oxygenation or aeration but the growth rate under both of them was the same. Although, treated fifth use water was significantly better than survival observed for trout in untreated fifth use water (35%). This study's results also showed DO was the dominant factor in limiting the performance under these systems. Although, difference in growth and survival in fifth use water may be oriented from enhancement of the other water parameters such as total dissolved solids or turbidity concentrations (Welker et al. 2019). Ta and Wei (2018) developed a model for prediction of DO concentration in recirculating aquaculture system (RAS) based on a convolution neural network. The results of the model showed that reverse understanding convolutional (CNN) neural network for its faster convergence in the pre-training period and better prediction stability is superior to BP. MSE for CNN and BP was 3, $21{,}258 \times 10^{-2}$ and 4.1686×10^{-3}, respectively. Ay and Kisi (2014) modeled COD (by using TSS, T, pH, flow rate, and COD data) and employed artificial neural networks (ANNs), fuzzy-neural adaptive inference system (ANFIS), and k-means clustering technique. Comparison results showed that the k-means-MLP (3.1,1) model with SS, T, pH inputs (RMSE = 65.77, $R^2 = 0.86$), performed better than other models in predicting daily COD concentration. The results of the model also showed that SS, T, and pH were highly effective parameters in daily COD modeling. Ahmed and Shah (2017) used ANFIS model to estimate BOD concentration in the Surma River of Bangladesh. The dataset contained ten water quality parameters including pH, alkalinity, hardness, TS, TDS, K^+, PO_4^{-3}, NO_3^-, BOD, and DO. The ANFIS model developed by using all variables had a very good performance ($R^2 = 0.8$).

Based on available previous studies, so far, a comprehensive model for assessing the impact of nutrition (feeding) and different biomass on consumption and required oxygen concentration in rainbow trout rearing systems has not been provided. Although rainbow trout mainly produced in flow-through raceway systems in the world and DO shortcoming identified as essential limiting factor in these systems, only a few studies such as Suárez et al. (2015) and Welker et al. (2019) investigated this issue in these systems. ANNs are the most widely used method for estimating water quality parameters. Artificial intelligence methods such as ANN have advantages of simplicity, high speed, and satisfactory results (Ghritlahre and Prasad 2018b; Messikh et al. 2017). The aim of the present study was to predict DO, BOD, and COD concentrations in an intensive rainbow trout rearing system by using MLP and RBF neural networks.

Materials and methods

Study area and data collection

Data were collected through continuous sampling during 3 months (from November to January 2017) twice a week from the seven selected stations of an intensive rainbow trout (*O. mykiss*) farm located in the region of Ortokand in Kalat County, Razavi Khorasan Province, Iran (“E”: 59°46′ and “N”: 36°59′) (Fig. 1). Each tank had dimensions of $30 \times 3 \times 2$ m^3, an effective 50-m^2 floor area and 2-m water depth. Input flow rate of each tank was 0.75 l S^{-1} and hydraulic retention time in the rearing tank was 5.7 days. All tanks were made of concrete materials and equipped with the same aeration system. There were seven stations including (a) 3000 5-g fish (0.08 kg M^{-3}), (b) 3000 25-g fish (0.41 kg M^{-3}), (c) 3000 50-g fish (0.83 kg M^{-3}), (d) 3000 100-g fish (1.66 kg M^{-3}), (e) 3000 220-g fish (3.66 kg M^{-3}), and (f) 2000 350-g fish (3.88 kg M^{-3}) and (g) 2000 830-g fish (9.22 kg M^{-3}). Feeding these fish was carried out manually three times a day (8 a.m., 13 p.m., and 17 p.m.). A schematic representation of the selected stations is shown in Fig. 2. In total, 175 samples were collected during the 3 months from selected stations.

Measured parameters

In the present study, parameters related to physicochemistry (DO, BOD, COD, and T), diet (CP and CF), fish (WG and B), and parameters related to experimental tanks (flow rate) were measured. CF (g) was based on the appetite of fish, and CP content (%) was determined by the Kjeldahl method ($N \times 6.25$) (AOAC 2006). WG was gained from the fish weighing method by a AND digital scale HL-I model with 0.01 g precision, and B was obtained by multiplying the number of fish by their average initial weight at each station. DO (mg L^{-1}) and T (°C) were measured by the portable multimeter model AZ-8603 with 0.01 precision. To measure flow rate, water was collected in a container with specific volume and by using a stopwatch (Abdullahi 2017). BOD and COD were measured by

Fig. 1 Picture of selected stations in the intensive rainbow trout system located in Artokand region, Kalat county, Iran

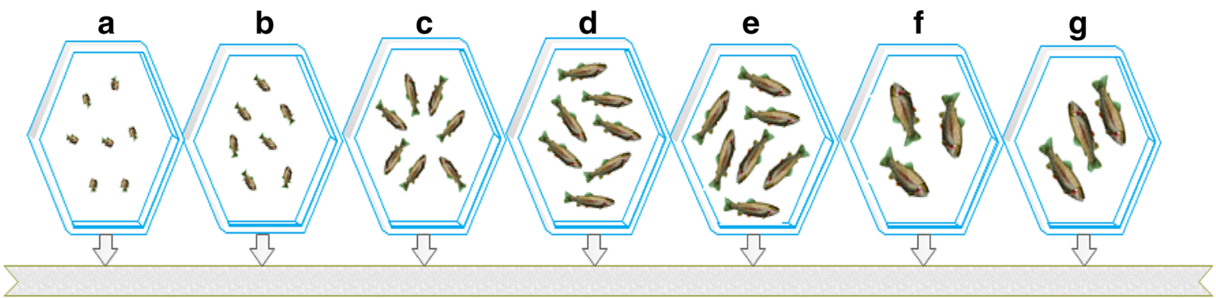

Fig. 2 Selected sampling stations from intensive rainbow trout farm. **a** Station with 5 g fish (0.08 kg/m^3). **b** Station with 25 g fish (0.41 kg/m^3). **c** Station with 50 g fish (0.83 kg/m^3). **d** Station with 100 g fish (1.66 kg/m^3). **e** station with 220 g fish (3.66 kg/m^3). **f** Station with 350 g fish (3.88 kg/m^3). **g** Station with 830 g fish (9.22 kg/m^3)

using BOD meter HANA model HI98193 with 0.01(mg L^{-1}) resolution through EPA standard method.

In this research, WG (g), B (g M^{-3}), CF (g), CP (%), flow rate (Q(l S^{-1})), and T (°C) were considered as inputs and DO (mg L^{-1}), BOD (mg L^{-1}), and COD (mg L^{-1}) were outputs of rainbow trout (*O. mykiss*) rearing system respectively.

MLP neural network

Multilayer perceptron neural network is the most widely used neural model for prediction which was inspired from actual structure of human brain, and like processor units include number of layers that contain neurons. These layers consist of three layers (an input layer, one or more hidden layers, and an output layer). Neurons performs task of transferring input data from input layer to output layer. This neuron set creates a neural network. Result of input weighing set makes output of each neuron. The set of input weights formed by each neuron is given by (1) (Ghritlahre and Prasad 2018a):

$$S = \left(\sum_{i=1}^{n} w_{ij}x_i\right) + b_j \tag{1}$$

Then, this set S passes through the activation function F and generates an output:

$$Y = F(S) = F\left(\sum_{i=1}^{n} w_{ij}x_i\right) + b_j \tag{2}$$

The "sigmoid function" is a non-linear activation function whose output is between zero and one. The sigmoid function is defined in the form of relation (3):

$$F(S) = \frac{1}{1+e^{-s}} \tag{3}$$

By using optimal algorithm, number of hidden layers and neurons in each layer can be determined. Question variables play an essential role in determining details of multilayer perceptron neural network structure and its connections. Training phase is used to create interconnections. The best model can be obtained by creating optimal network structure through appropriate algorithm (Mendez-Santiago and Teja 2000). Figure 3 shows structure of multilayer perceptron neural network.

During training period, the error between actual and predicted values is minimized through frequent adjustment of weights and biases by the learning algorithm. The most commonly used learning algorithms include SCG, CGP, BFG, and LM. LM algorithm is preferable

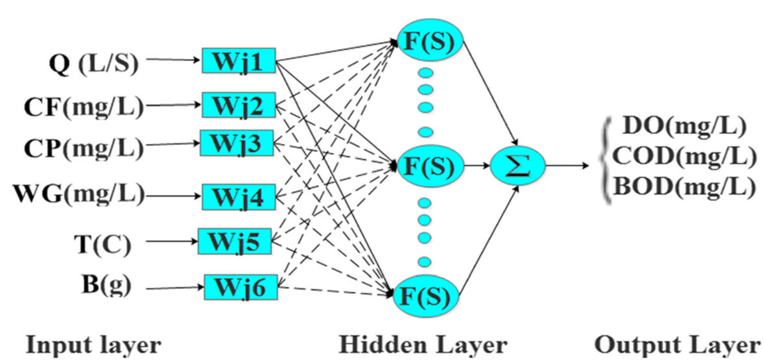

Fig. 3 MLP neural network structure with an input layer, a hidden layer, and an output layer

because it is faster than other training algorithms (Ghritlahre and Prasad 2018b).

RBF neural network

RBF neural networks is a feed-forward network that uses the supervised training manner (Karri 1999) and consists of three layers (input layer, hidden layer, and output layer) (Fig. 4). The input layer connects the inputs to the network. The hidden layer carries out a non-linear transmission from input space into the output space. The output layer applies a linear transfer from the hidden space to the output space.

RBF neural network is a symmetric radial basis function and its response always adjusts with the change of distance from a central point (Cowper et al. 2002). The positive features of the RBF neural network are the fast-learning, the possibility of training with the least initial dataset, the optimal network size determination by the algorithm itself, and the absence of the local minimum problem. Among several radial basis functions, application of the Gaussian function is more common, which is presented as follows:

$$\varphi(x, \mu) = e^{\frac{\|x-\mu\|^2}{2d^2}} \qquad (4)$$

The μ center of Gaussian function (mean value x) and d distance from the center φ (x, μ) obtain the measure of the spread of Gaussian curve. Distance x from the center of μ determines the output of each hidden unit. In the training process, the μ center and the d spread are parameters to be determined. A hidden unit has higher sensitivity to data points near the center. This sensitivity can be adjusted by controlling the d-index. Modeling map complexity determines the number of radial basis functions in the hidden layer, not the size of the dataset (El-Shafie et al. 2010).

Performance evaluation criteria

In order to evaluate the performance of the models, statistical criteria such as root mean square error (RMSE), coefficient of determination (R^2), and mean absolute percentage error (MAPE) were used (Taki et al. 2016; Zendehboudi and Tatar 2017):

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(y_{act}-y_{est}\right)^2}{n}} \qquad (5)$$

$$R^2 = 1-\frac{\left(\sum_{i=1}^{n}\left(y_{act}-y_{est}\right)^2\right)}{\sum_{i=1}^{n}\left(y_{act}-\mathrm{y}_{act}\right)^2} \qquad (6)$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_{act}-y_{est}}{y_{act}}\right| \times 100 \qquad (7)$$

where y_{act} is the observed values, y_{est} is the predicted value, and n is the total number of data. The model with lowest RMSE, MAPE, and highest R^2 was considered as the best model.

Results

In the present study, two methods of MLP and RBF neural networks were used to estimate differences in the concentration of DO, BOD, and COD in rainbow trout production tanks.

The most suitable neural network model and evaluation

Prediction performance of the neural networks depends on the type of training algorithm, the size and quality of the dataset used in the training phase, and the neural network method itself. Two training algorithms Trainbr and Trainlm

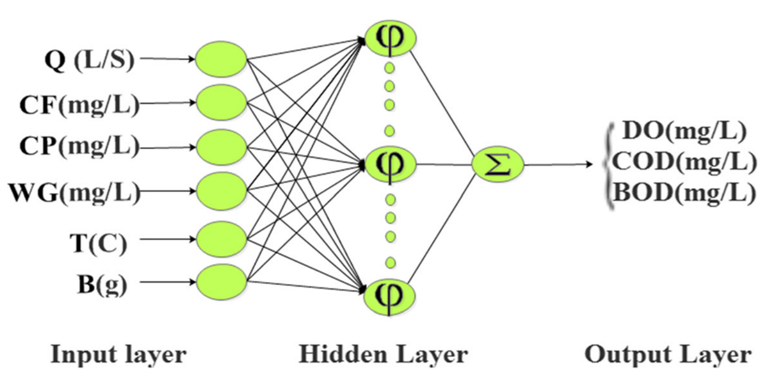

Fig. 4 RBF neural network structure with an input layer, a hidden layer, and an output layer

and two sizes of training sets, including 80% and 40% of the total data, were used for evaluation and comparison of two RBF and MLP neural networks. Since the less standard deviation of errors indicates the higher stability of the network and the sizes of training sets indicate generalizability, the smallest mean values and standard deviation of RMSE and MAPE of the MLP neural network by two different sizes of training sets in the prediction of DO, BOD, and COD concentrations are shown by blue and red colors in Table 1. In the same manner, results of RBF neural network evaluation are illustrated in the Table 2. The results of this study indicated that although both types of neural networks can be used to estimate changes in DO, BOD, and COD concentrations, RBF neural network for its better stability and generalizability has a relative superiority to MLP. The average RMSE and MAPE of the RBF neural network achieved from the application of the five-fold method (20 different sets of data in the training and testing phase) were less than 1.2% and 3%, respectively, for DO, BOD, and COD concentrations prediction.

The results of assessment of the agreement between the observed and predicted concentrations of the three DO, BOD, and COD parameters by RBF neural network for the two sizes of training sets of 80% and 40% are presented in Fig. 5a, c, e, b, d, f, respectively. As the results confirmed, there was a very good agreement between the two observed and predicted datasets ($y = 0.99x + 0.00$). Therefore, the neural network has been well able to fit the relationship between dependent and independent studied variables.

Sensitivity analysis

Sensitivity analysis technique was used to study the effect and significance of each independent variable on estimated neural network output variables. The result of the sensitivity analysis showed that the CF parameter showed the greatest effect in estimating the DO concentration change in the tanks. Its elimination extremely increased percent of error (MAPE) (Table 3 part DO). The results of the BOD model's sensitivity analysis showed that independent variables CF, CP, WG, and B have the most to the least ranking effect on the estimation and output variation of the model (Table 3 part BOD). The results of the COD model's sensitivity analysis also showed that all independent input variables affect the estimation error of COD. In addition, the variables B, T, WG, CF, CP, and Q have the most to the least effect on COD variation (Table 3 part COD).

Table 1 Evaluation of the generalizability of MLP regression models for different cutouts in terms of the size of the calibration dataset (TS) for the intensive rainbow trout culture system with different biomass

TS* (%)			Train		Test		Total	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
80	DO	MLP1	0.05±0.02	10.95±5.58	0.05±0.02	10.85±6.92	0.05±0.02	10.96±5.37
		MLP2	0.00±0.00	0.63±0.10	0.00±0.00	0.68±0.19	0.00±0.00	0.64±0.06
	BOD	MLP1	0.12±0.04	9.95±3.82	0.13±0.05	11.19±7.61	0.12±0.04	10.20±4.25
		MLP2	0.03±0.01	0.72±0.25	0.03±0.03	0.83±0.03	0.04±0.00	0.74±0.23
	COD	MLP1	0.92±0.30	50±36	0.93±0.33	47±37	0.93±0.29	50±35
		MLP2	0.32±0.19	7.33±6.57	0.49±0.25	8.07±6.40	0.38±0.14	7.48±6.43
40	O2	MLP1	0.04±0.01	10.64±5.69	0.06±0.02	12.96±12.89	0.05±0.02	12.03±8.15
		MLP2	0.00±0.00	0.57±0.11	0.00±0.00	0.78±0.11	0.00±0.00	0.70±0.06
	BOD	MLP1	0.09±0.03	10.05±5.30	0.13±0.04	10.82±5.37	0.12±0.03	10.51±4.74
		MLP2	0.03±0.02	1.39±1.02	0.04±0.01	1.45±0.91	0.04±0.00	1.43±0.90
	COD	MLP1	0.97±0.38	57±32	1.21±0.44	61±47	1.13±0.40	59±37
		MLP2	0.31±0.11	9.53±5.62	0.55±0.08	11.87±5.90	0.48±0.08	10.93±5.14

*The size of the selected data at the training stage, MLP1 and MLP2 were trained by Trainlm and Trainbr, respectively.

Blue and red colors respectively are indicative of the smallest mean values and standard deviation of RMSE and MAPE of the MLP neural networks by two sizes of training sets 80% and 40% in the prediction of DO, BOD and COD concentrations.

Table 2 Evaluation of the generalizability of RBF regression models for different cutouts in terms of the size of the calibration data set (TS) for the intensive rainbow trout culture system with different biomass

TS* (%)			Train		Test		Total	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
80	DO	RBF1	**0.00±0.00**	**0.50±0.05**	**0.00±0.00**	**0.50±0.13**	**0.00±0.00**	**0.50±0.02**
		RBF2	0.00±0.00	0.53±0.05	0.00±0.00	0.52±0.15	0.00±0.00	0.53±0.02
	BOD	RBF1	0.01±0.00	0.65±0.22	0.01±0.01	0.66±0.49	0.01±0.01	0.65±0.17
		RBF2	**0.01±0.00**	**0.27±0.06**	**0.01±0.01**	**0.28±0.12**	**0.01±0.01**	**0.27±0.06**
	COD	RBF1	0.07±0.04	2.47±0.64	0.07±0.04	2.49±2.19	0.08±0.03	2.48±0.46
		RBF2	**0.03±0.01**	**0.78±0.20**	**0.03±0.01**	**0.80±0.55**	**0.03±0.01**	**0.78±0.14**
40	O2	RBF1	0.00±0.00	0.51±0.09	0.00±0.00	0.49±0.07	0.00±0.00	0.49±0.03
		RBF2	0.00±0.00	0.53±0.09	0.00±0.00	0.52±0.16	0.00±0.00	0.53±0.02
	BOD	RBF1	0.01±0.00	0.55±0.27	0.01±0.01	0.54±0.28	0.01±0.01	0.54±0.23
		RBF2	0.01±0.01	0.29±0.11	0.01±0.01	0.26±0.05	0.01±0.01	0.27±0.07
	COD	RBF1	0.11±0.07	2.09±1.23	0.11±0.06	1.49±0.82	0.11±0.06	1.73±0.78
		RBF2	0.05±0.03	0.91±0.37	0.05±0.03	0.74±0.26	0.05±0.03	0.81±0.19

*The size of the selected data at the calibration stage, RBF1 and RBF2 were trained by Trainlm and Trainbr, respectively.

Blue and red colors respectively are indicative of the smallest mean values and standard deviation of RMSE and MAPE of the RBF neural networks by two sizes of training sets 80% and 40% in the prediction of DO, BOD and COD concentrations.

Effect of input parameters on oxygen consumption and demand

Based on the sensitivity analysis results, for each of the three DO, BOD, and COD models, the best set of effective variables was selected. The individual effects of the parameters are important, but the final result was acquired from a simultaneous examination of the interactions between these parameters. In this way, variation in the BOD concentration versus CF and CP, WG, and B values is shown in Fig. 6a–c. BOD level increased by increasing CF versus increasing WG and B quantity in the rainbow trout tanks, but increasing CF versus CP somewhat decreased BOD concentration. The same results were achieved for COD variation and are indicated in Fig. 7a–c. In general, B increased in tanks, which was associated with an increase in CF, significantly increased the BOD and COD concentrations, and created critical conditions for aquatic life.

Discussion

The results showed that the RBF neural network with less than 3% error for prediction of the oxygen concentration was more successful. CF, B, and WG were the most important factors that affected the changes of oxygen consumption and demand in the system. The increase in the values of these parameters over time reduced the DO concentration and increased BOD and COD concentrations. Huan et al. (2018) developed the hybrid model based on ensemble empirical decomposition mode (EEMD) and LSSVM to predict the DO concentration in aquaculture for the next 24 h. Initially, DO time series by EEMD was decomposed into two groups. Then, the decomposed subsequence was reconstructed by phase space reconstruction (PSR), and then an LSSVM model was optimized by the Bayesian evidence framework of each subsequence. Finally, the BP neural network was used to reconstruct the predicted values of each component. Their results showed that the model with 0.021 as error had good estimation performance. Ta and Wei (2018), in a study, tried to predict the DO concentration in recirculating aquaculture system using two CNN and BP neural networks. Four parameters, DO, T, EC, and pH, were used as input parameters. These models were able to estimate the DO concentration

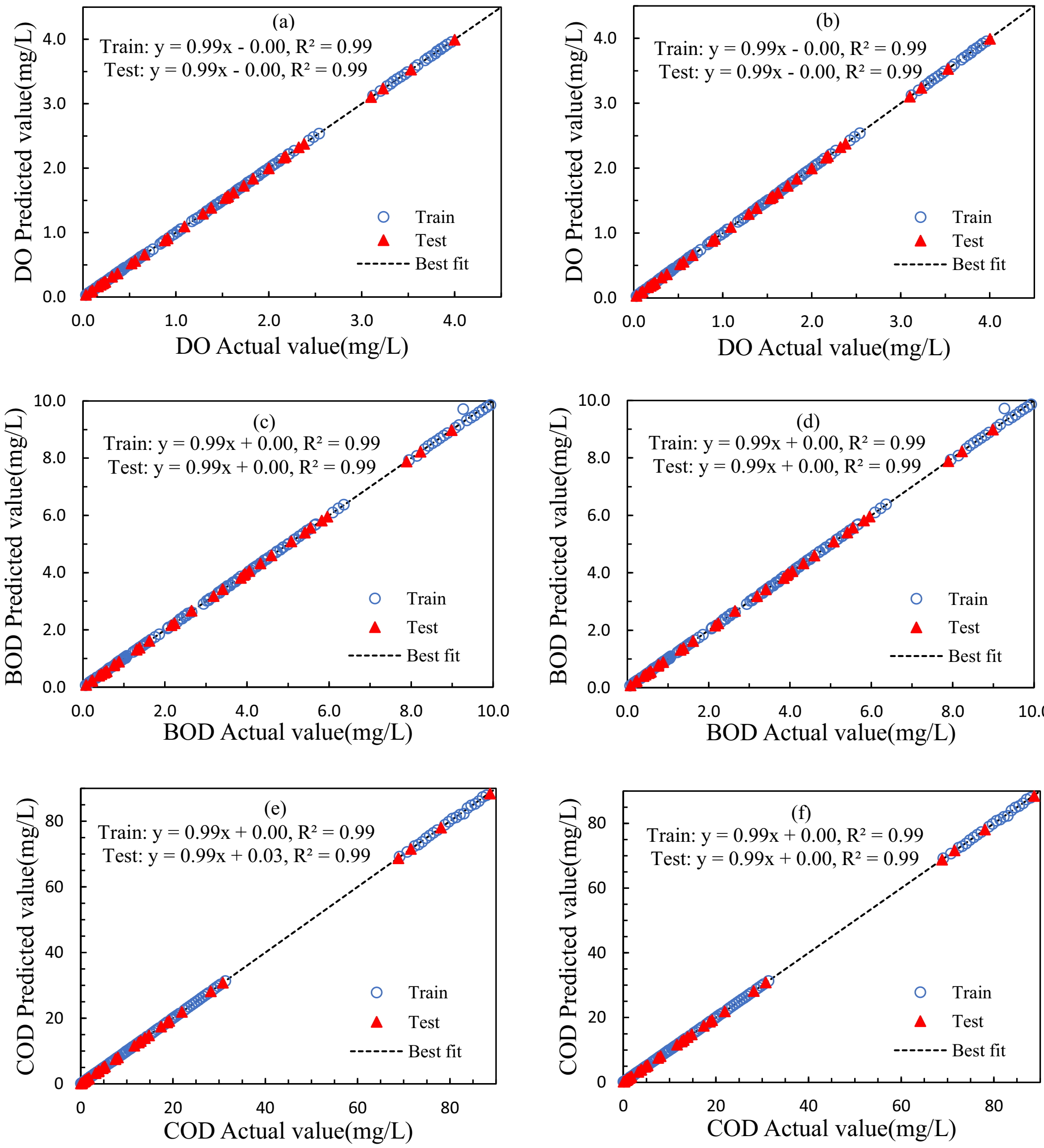

Fig. 5 Evaluation of the agreement between actual and predicted values of DO, BOD, and COD of RBF neural network models with two sizes of training sets of 80% (**a**, **c**, **e**) and 40% (**b**, **d**, **f**) for the intensive rainbow trout culture system with different biomass

with a precision of 0.002 and 0.004. However, CNN's neural network was preferred to BP's neural network due to faster convergence in training and better sustainability.

Although, there are major differences between open systems such as understudy system and RAS system. In RAS system, nitrification process reduces ammonia concentration through using biological filters. The nitrifying bacteria are considered as fuel of this process. They attach themselves on width surface area aerobic biofilters provided for them, where nitrate is obtained from nitrite as final product of total ammonia oxidation. In this process, at first, carbonic acid is formed through combination of hydrogen ions with carbon dioxide and lowers the pH of the water. While the ratio of organic carbon to ammonia/nitrogen ($C\ N^{-1}$) is relatively high, heterotrophic bacteria consume ammonia/nitrogen; they also increase microbial biomass through assimilation of organic waste products and convert them to microbial biomass. For each gram of ammonia oxidized to nitrate in the nitrification process, 4.18 g of dissolved oxygen and 7.04 g alkalinity (CaCO3) are consumed. Factors

Table 3 Sensitivity analysis result of RBF neural network model for the intensive rainbow trout culture system with different biomass

		RMSE	MAPE	R^2
DO	All	0.00	0.63	0.99
	All exclude Q	0.00	0.60	0.99
	All exclude CF	**0.10**	**14.24**	**0.99**
	All exclude CP	0.00	0.59	0.99
	All exclude W	0.00	0.63	0.99
	All exclude T	0.00	0.71	0.99
	All exclude B	0.00	0.61	0.99
BOD	All	0.05	1.73	0.99
	All exclude Q	0.03	0.87	0.99
	All exclude CF	**0.12**	**5.60**	**0.99**
	All exclude CP	**0.04**	**1.50**	**0.99**
	All exclude W	**0.04**	**1.34**	**0.99**
	All exclude T	0.04	0.63	0.99
	All exclude B	**0.04**	**1.32**	**0.99**
COD	All	0.19	2.26	0.99
	All exclude Q	**0.26**	**3.21**	**0.99**
	All exclude CF	**0.99**	**17.76**	**0.99**
	All exclude CP	**0.37**	**10.71**	**0.99**
	All exclude W	**2.02**	**19.85**	**0.99**
	All exclude T	**2.06**	**25.40**	**0.99**
	All exclude B	**1.75**	**36.12**	**0.99**

The most important independent variables on estimated of DO, BOD and COD concentrations respectively, were bolded

that influence biofilter performance are total ammonia nitrogen, organic carbon, alkalinity and pH, temperature, and carbon dioxide. Denitrification of unaerobic process is carried out after nitrification to compensate the limitations. Denitrification is affected by factors such as nitrate, oxygen, pH, temperature, and organic carbon (Gichana et al. 2018).

These models and similar models considered only physical and chemical factors of water quality in the rearing system with constant stocking density. There was no mention of nutrition, protein percentage, and stocking density in the system, and the effect of these factors on the change of DO concentration was ignored. All of these models only predict the DO concentration, and BOD and COD, which play an important role in changing the amount of DO and contaminants in the wastewater of cultivating systems, were neglected. A few studies such as Suarez et al. (2015) evaluated the effect of stocking density and fish diet energy level on oxidative status of rainbow trout, and their results showed that increasing stocking density and diet energy level simultaneously decreases DO concentration and creates high stress in the system. The importance of evaluation of stocking density and fish diet effect on oxygen concentration variation is manifested from such study results.

There was a high association between water quality and aquatic nutrition. Ammonia is the principal product of fish protein catabolic and takes part in the feed decomposition. According to studies, tiny particles constitute 60% of the food in aquaculture systems. Oxygen consumption, ammonia, and other toxic substance production occur as a result of these edible product decomposition, which jeopardizes fish welfare; also, filtration and aeration equipment tolerate heavy load (Chang et al. 2005). On the other hand, lack of control of the gradual reduction of DO concentration after feeding, especially in intensive rearing tanks, and abrupt deaths to fish will cause serious detriment (Wu et al. 2015). Changes in the concentration of water quality parameters can also affect

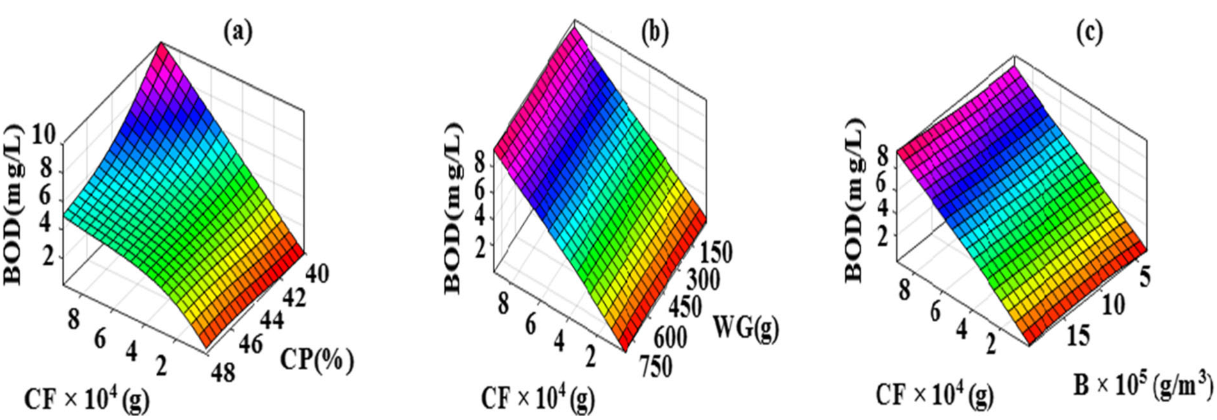

Fig. 6 BOD concentration changes versus CF and CP (**a**), WG (**b**), and B (**c**) values in the intensive rainbow trout culture system with different biomass

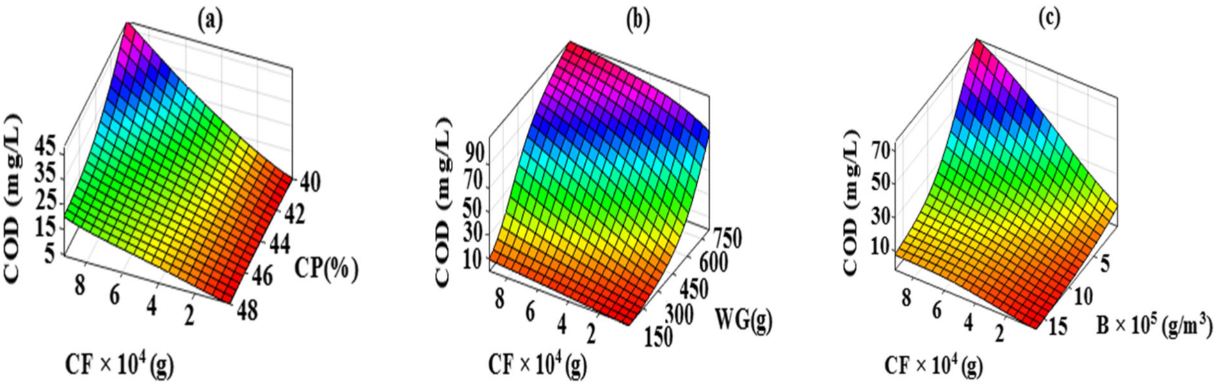

Fig. 7 COD concentration changes versus CF and CP (**a**), WG (**b**), and B (**c**) values in the intensive rainbow trout culture system with different biomass

fish appetite. T and DO are two very important parameters. This information can be used as input for an intelligent control model to provide accurate amounts of food (Soto-Zarazúa et al. 2010). Zhou et al. (2018)'s results showed that in the event of reduced water pollution and welfare enhancement, an intelligent food control approach based on the ANFIS model would be able to make production affordable by reducing food waste. Wu et al. (2015) stated that when the fish were looking for food, its activity caused a change in the DO concentration which can be used to quantify nutritional behavior. The feeding behavioral measurement indicator was used as an input for the ANFIS model to recognize the control of feeding. Early water quality studies for aquaculture revealed that increasing stocking density has a negative effect on water quality parameters such as decreasing DO concentration and increasing ammonia, nitrate, and carbon dioxide concentrations (Fivelstad and Binde 1994; Fivelstad et al. 1995; Fivelstad et al. 1998). Although many factors affecting oxygen concentration variations in rainbow trout rearing has been considered in this paper, factors related to seasonal variation (light intensity, photoperiod, and light spectrum) need to be considered in the long term too. Since oxygen is part of the time series, in order to increase the accuracy of neural network models, it is recommended to select shorter sampling intervals in future studies to obtain better results.

Conclusion

In the present study, MLP and RBF neural networks were used to predict the amount of consumable oxygen and needed in an intensive rainbow trout production system by different B. Fivefold method, different sets of training size, and different learning algorithms were used to evaluate the models. Results indicated that RBF neural network due to higher stability and generalization was preferable to MLP neural network. The average RMSE and MAPE of the RBF neural network was less than 0.12% and 3% in DO, BOD, and COD concentration estimation. Based on the results of this study, CF was identified as a key factor in altering DO and BOD and COD concentrations. In addition to CF, CP, WG, and B had significant effect on the change in BOD and COD values, which should be taken into account by aquaculturists in decision-making about stocking density and feeding.

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