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Full Length Research Paper

Impact of enhanced flow on the flow system and wastewater characteristics of sewage-fed fisheries in India

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In this study, we estimated the impact of enhanced flow on shallow wetlands that receive major effluent discharge from an adjoining metropolitan city. The local people use the shallow wetlands for pisciculture. Beginning in 1998, the population of the city began to rise and the amount of effluent discharge increased. The excess load is now a problem for the city engineers, and they plan to manage the sewage by increasing the area of the sewage network. The depth of the wetlands is also decreasing due to an increase in suspended solids. The quantity of the toxic load suspended in the discharge has increased the silt content, which has consequently further reduced the depth of the wetlands. The excess flow on low depth wetlands may cause overflows and destroy both the ecosystem and the livelihood of the local people. In this study, the pattern identification capability of neuro-genetic models was used to estimate the impact of the excess flow on sewage-fed wetlands. Two neural network models were created to estimate whether fisheries can accommodate the enhanced flow. According to the results of this study, the East Kolkata Wetlands, India can accommodate 1450 million litres per day (MLD) of sewage, if the average depth of water is increased to 1.18 m.

Key words: Dry weather flow, East Kolkata wetlands, neural network, sewage-fed fisheries.

INTRODUCTION

Humans often deal with their waste by using instituted waste management systems in both pre-modern and modern forms. However, with global industrialization and population explosion, waste production has increased dramatically, endangering the environment and threatening humans and other living organisms (WHO, 2006). The environmental issues caused by human waste stress the importance of waste management. Archeological evidence shows that humans successfully managed their waste before landfills and incinerators were developed (WHO, 2006). At many archeological sites, dumping pits were discovered where early people likely deposited their waste. In the course of history, waste regulations were enacted. This trend throughout history suggests that waste management is not a modern principle, but is rather a natural response to existence.

The United Nations Economic and Social Development Division of Sustainable Development included environmentally sound management of solid waste as one of the “environmental issues of major concern in maintaining the quality of the earth's environment and, especially, in achieving environmentally sound and sustainable development in all countries” (Section II, Agenda 21 of Conservation and Management of Resources for Development). The effluent discharge of metropolitan cities is expected to increase with a continued increase in population. Engineers in China, Bangladesh and many other countries where the population increase is unchecked face the problem of an increasing population and its impact on city sewage networks. East Kolkata wetland was declared a Ramsar Site[1] with wetlands of international importance, in 2002.

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[1]The Convention on Wetlands (Ramsar, Iran, 1971) of International Importance, called the Ramsar Convention, is an intergovernmental treaty that provides the framework for national action and international cooperation for the conservation and wise use or sustainable use of all of the wetlands.

The East Kolkata wetlands and their importance

Kolkata was founded in the year 1690 and has slowly grown in an uncontrolled manner along the eastern side of the Ganga (Hooghly) River, stretching to the north and south. The eastern part of Kolkata was chosen by the city managers as a place to receive both liquid and solid waste. The dry weather flow from the core area of Kolkata is discharged in a dedicated dry weather flow (DWF) channel that moves to the east through the East Kolkata Wetlands (EKW) until it meets the Kulti River. Presently, the Kolkata Municipal Corporation (KMC) has reported a dry weather flow of approximately 1000 MLD leading to the DWF channel.

In 2002, the man-made EKW was declared a Ramsar wetland based upon the wise use of the wetland, in particular sewage treatment, fish farming and agricultural irrigation. The East Kolkata Wetlands are the largest area of sewage fed-aquaculture in the world. The sewage-fed aquaculture system acts as an ecologically balanced wastewater treatment plant. The system refines the effluent to an acceptable quality before discharging into the island surface waters. Furthermore, there is an enhanced production of fish to a level at least four times the production of fish in normal surface water (ADB, 2008; Jadavpur University, 2007). The wastewater in the EKW is therefore considered a resource rather than a pollutant (Raychaudhuri et al., 2008). The total area of the EKW is 12741.30 ha and is comprised of 364 sewage-fed fisheries, multiple agricultural areas, garbage disposal sites, urban development areas, rural settlement areas and several other bodies of water. The total water area is approximately 5852.14 ha.

Prior to 1930, the main source of water for the fisheries was the tidal Bidyadhari River. The silting of this river eliminated tidal waters and the entire area became a vast derelict swamp. There was a desperate need for an alternate source of water for the traditional fisheries in these wetlands. Thus, the city sewage was considered for use in these fish ponds. With the entry of sewage from the city into these areas, the salinity decreased considerably and the wetlands became ideal for freshwater pisciculture.. Presently, 67% of water is used for sewage-fed fish farming (ADB, 2008; Jadavpur University, 2007). The maximum yield from these sewage-fed fisheries is approximately 30000 metric tonnes (MT) per year. The average yield prior to sewage-fed fisheries from wetlands during recent years may be 80% of the maximum yield (that is, 24000 MT/year). The wastewater aquaculture system receives 70 to 75% of untreated sewage per day. The estimated productivity of aquaculture is approximately 6 to 7.5 MT per ha each year for areas receiving wastewater. It is expected that the flow in the DWF channel will increase to approximately 1200 MLD in the near future due to the extension of sewage networks in many areas of KMC. The additional sewage load may have an impact on the quality of wastewater in the DWF channel. Furthermore, the increased sewage load may influence the existing wetlands, where a major part of the wastewater is diverted for pisciculture. There is also concern that the quality of the effluent of the DWF discharging into the Kulti River may not meet the prescribed standard due to this planned additional discharge. According to the Jadavpur University (2007) report, the ponds produce an average 6 tonnes of fish/ha/annum. Mara et al. (1993) anticipated, with a loading of total nitrogen of 4 kg/ha/d, carp and tilapia yields could be in the order of 13 tonnes/ha/annum, assuming that the ponds are drained and harvested three times a year, that there is a fish loss of 25%. Mara (1997) found that 70 to 90% of the BOD of the final effluent from a series of well designed WSP is due to the algae it contains and “algal BOD” is very different in nature from “sewerage BOD”. The filtered BOD concentration from these ponds would easily meet discharge requirements of 30 mg/L. Mara (2003) stochiometrically described the production of oxygen where 1 g of algae produces 1.55 g/L of dissolved oxygen which oxidizes 1 g/L of BOD. Design criteria for wastewater-fed aquaculture ponds were summarized by Polpasert and Koottatep (2005). Polpasert and Koottatep (2005) found organic loads up to 75 kg/ha/d were acceptable for such wastewater-fed fish ponds.

Sadhukhan et al. (1996) measured the mercury concentration in sediments, water and fish from the East Kolkata wetland. It was observed that the mercury content of the fish obtained from these water bodies were below the permissible safe dietary level of 0.5 mg/kg while they purify the water and praised the natural system of the wetlands for accommodating the total sewage flow of one of the five most populated cities of the world.

Artificial neural network (ANN) and wetlands

An ANN is a flexible mathematical structure that is capable of identifying complex nonlinear relationships between input and output datasets (Majumder et al., 2007). In recent years, ANNs have been successfully applied to the modeling and forecasting of time series and offer a relatively quick and flexible means for modeling. As a result, the application of ANN modeling is widely reported in the hydrological studies (Neelakantan and Pundarikanthan, 2000; Ray and Klindworth, 2000). In the context of hydrological forecasting, recent studies have reported that ANNs may offer a promising alternative for rainfall runoff modeling (Hsu et al., 1995; Fernando and Jayawardena, 1998; Tokar and Johnson, 1999; Elshorbagy and Simonovic, 2000; Liong et al., 2001) and stream flow prediction (Clair and Ehrman, 1998; Imrie et al., 2000). ANN was applied to reservoir inflow forecasting by Jain et al. (1999) and Coulibaly et al. (2000).

Additionally, ANN has been used for the prediction of

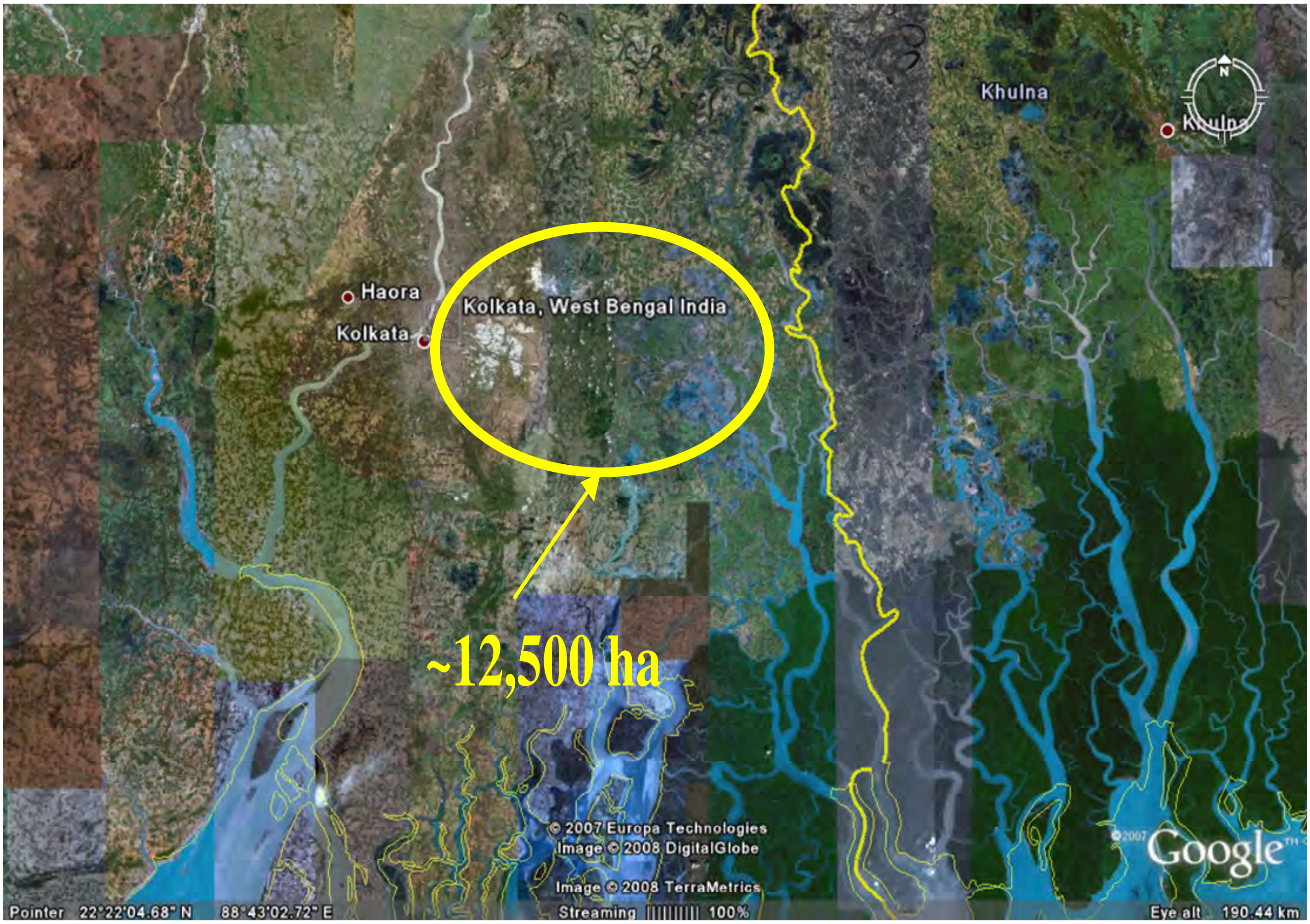

Figure 1. Location of East Kolkata wetlands west of Kolkata, West Bengal, India

water quality parameters (Maier and Dandy, 1999) and as an estimator of reference evapo-transpiration rates (Odhiambo et al., 2001; Kumar et al., 2002). These applications use different types of neural networks, but they all provide better results than conventional models. Majumder et al. (2007) attempted to classify and locate the optimal use of available water in a multi-dimensional catchment due to the categorization capability and flexibility in development of such networks. Ghedira et al. (2000) attempted to classify wetlands with the help of ANN and a multi-temporal dataset of RADARSAT images. Here, we applied ANN to analyze whether the enhanced flow in the EKW will have any impact on water quality and wetland characteristics. Neural models are built for this purpose due to their flexibility and reliability in predicting unknown and non-linear problems.

Study area

The study area was extended from Topsia Point to Ghusighata of the EKW (Figure 1). The DWF channel and its sewage-fed fisheries were also studied. Both primary and secondary monitoring data were considered in the analysis. In the total stretch of DWF, six locations (Topsia Point, Ambedkar Bridge, Bantala FFC, Bamanghata, Karaidanga and Ghusighata) were selected for flow and water quality monitoring (Figure 2). The three fisheries loops (DWF–fishery network that is Chachcharia Fishermen Co-op Soc Ltd, Nalban Fisheries Co-op Soc Ltd and Dhali-Bheri Co-op Soc Ltd) in Figure 2, highlight the utilization of sewage in the fisheries that were included in the study. The characteristics of the selected fisheries are depicted in Table 1.

Objectives

In the near future, it is expected that the flow in the DWF channel will increase to approximately 1200 MLD due to the extension of sewerage networks in many areas of KMC and to enhance the economic benefit for all

Figure 2. Sampling sites in dry weather flow (DWF) channel and the fish ponds in EKW. Sample locations: 1) Topsia, 2) Ambedkar Bridge, 3) Bantala, 4) Bamunghata, 5) Nalban, 6) Chachchria, 7) Dhalibheri, 8) Karaidanga and 9) Ghusighata. Canals and rivers: A) storm water flow (SWF), B) dry weather flow (DWF), C) Bagjola Khal (canal) and D) Kulti River.

stakeholders of the EKW (Fish Producers Association (FPA), Save Wetlands Committee (SWC), Labour Unions, etc.), supporting the sustainable livelihoods of the community without hampering ecologically balanced wetlands. The present study analyzed the impact of excess flow on the water volume of the sewage ponds based on the depth and the catchment area of the ponds, by using two neural network models. The additional sewage flow to these ponds will enhance the continued wise use of this facility. The additional sewage load in conjunction with some remedial measures to the existing channel system will potentially enhance fish production by providing additional flow (that is additional fertilizer) for the pond system. The additional sewage flow is predicted to meet WHO guidelines for wastewater-fed aquaculture and irrigation for agriculture. Discharge standards into inland waters will still be met.

ARTIFICIAL NEURAL NETWORKS (ANN)

Neural networks provide model-free solutions. The mathematical representation of an ANN model of n input neurons (Table 2) ($x_1,x_2,...x_n$), h hidden neurons (Table 3) ($z_1,z_2,…z_n$) and m output neurons (Table 2) ($y_1,y_2,...y_n$) is shown by Equation 1. In the equation, t_j is the bias for neuron z_j and f_k is the bias for neuron y_k. Additionally, w_{ij} is the weight of the connection from neuron x_i to z_j and beta is the weight of the connection from neuron z_j to y_k. The function that ANN calculates is:

$$y_k = g_A\ (\sum z_j b_{jk} + f_k)....(\ j = 1 - h\ ) \quad (1)$$

in which

$$z_j = f_A\ (\sum x_i w_{ij} + t_j).....(\ i = 1 - n\ ) \quad (2)$$

where g_A and f_A are the activation functions (Sudheer, 2005).

Selection of network topology

There are different types of neural networks, including feed forward, radial basis function and time delay lag network (TDLN). The type of network is selected with respect to the knowledge of input and output parameters and their relationships. The topology network was selected as per the amount and type of training datasets. A method of trial and error is generally used for this purpose, but many studies now prefer the application of a genetic algorithm (Ahmed and Sharma, 2005). Genetic algorithms are search algorithms based on the mechanics of natural genetics and natural selection. A genetic algorithm is a robust method of searching for the optimum solution to a complex problem where it is difficult or impossible to test for optimality. Although the basics of GA have already been discussed by some authors (Ahmed and Sarma, 2005; Wang, 1991; Wardlaw and Sharif, 1999), the details of the basic procedures of GA are not clear. GA was used in the present study to search the ideal topology for the neural models.

Training phase

To encapsulate the desired input-output relationship, weights of each input were adjusted and applied to the network until the desired error was achieved. This is called “training the network.” There are multiple training algorithms available. Among these methods, back-propagation (ASCE, 2000) is most commonly used. In the present study, quick propagation (QP) and conjugate gradient descent (CGD), both derived from basic back-propagation algorithms, were used as the training algorithm. Quick propagation is a heuristic modification of the back-propagation algorithm created by Fahlman (1983). This training algorithm treats the weights as if they are quasi-independent and attempts to use a simple quadratic model to approximate the error surface.

In spite of the fact that the algorithm has proven to be much faster than the standard back-propagation in many

Table 1. Characteristics of selected fisheries in EKW.

Selected fisheries in EKW	Land area (ha)	Area of pond (ha)	Depth of pond (average) (mm)	Hydraulic load of sewage in wet season (m^3/ha/day) (residence time in days)	BOD Loading rate (kg/ha/day)	Total fish production (MT/year)	Fish production per ha (MT/year/ha)
Chachcharia Fishermen Co-op Soc., Ltd.	55.0	44.00	965	134 (74) Dry season residence time was 16 days	11.2 Dry season BOD loading rate was 50 kg/ha/day	300	6.8
Nalban Fisheries Co-op Soc., Ltd.	18.8	16.92	1,067	357 (28)	30	85	5.0
Dhali-Bheri Co-op Soc., Ltd.	6.7	6.03	1,016	286 (35)	24	40	6.6

situations. The CGD is an advanced method for training multi-layer neural networks. It is based on the linear search usage in the line of an optimal network weight change. Thecorrection of weights is conducted once per iteration. In most cases, this method works faster than back- propagation and provides more precise forecasting results (Hassoun, 1995). Because the relationship between input and output parameters in the present study was non-linear, the QP and CGD advanced algorithms were used to train the models.

Testing phase

A portion of the available historical dataset was fed to the trained network and a known output was estimated from this portion. The estimated values were compared with the target output to find a MSE. If the value of MSE was less than 1%, the networks were considered to be sufficiently trained and ready for estimation. Some sections of the dataset were also used for cross-validation so that the network was not over-trained during the training phase.

Evaluation of the network

The accuracy of the results obtained from the network can be assessed by comparing the response with the validation set. The commonly used evaluation criteria include the percentage mean square error (MSE; Equation 3), the correlation coefficient (r; Equation 4), the coefficient of efficiency (C.E; Equation 5) and the standard deviation (Standard deviation (S.D); Equation 6)

$$\text{MSE} = \sum_{1}^{n}\left((Tp - Op)^2 / n\right) \tag{3}$$

$$r = \left[\sum((Tp - Tm)(Op - Om)) / (\sum_{1}^{n}(Tp - Tm)^2 \sum_{1}^{n}(Op - Om)^2)^{1/2}\right] \tag{4}$$

$$\text{C.E.} = 1 - \left(\sum_{1}^{n}(Tp - Op)^2 / \sum_{1}^{n}(Tp - Tm)^2\right) \tag{5}$$

$$\text{S.D} = \frac{\sum_{1}^{n}(Tn - \overline{T}n)^2}{n} \tag{6}$$

where, Tp and Tn are the target values for the p^{th} and n^{th} patterns, respectively, Op is the estimated value for the p th pattern, Tm is the mean target, Om is the estimated values and n is the total number of patterns.

The MSE shows the measure of the difference between the target (Tp) and estimated (Op) value, and r defines the degree of correlation between two variables. The C.E. criterion is the basis of standardization of the residual variance with initial variance (Nash and Sutcliffe, 1970). In this criterion, a perfect agreement between the observed and estimated output, yields an efficiency of one. A negative efficiency represents lack of agreement and no agreement means the estimated values are equal to the observed mean. S.D is the measure of the deviation of the estimated value from the target output. A perfect match between the observed data and model simulations is obtained when the S.D approaches zero (Yitian and Gu, 2003).

METHODOLOGY

Two models per wetland area were developed with the help of neuro-genetic models. The input and output variables considered are depicted in Table 2. Flow at different sampling points through the DWF channel and the depth at the sewage pond was considered to be input and the flow at the same venue was considered to be the output. Such models were also developed for Nalban and

Table 2. Summary of inputs and outputs for the models developed from Conditions 1 and 2 (Models) AQP1, AQP2 and BCGD1 and BCGD2.

Condition			Inputs	Outputs
	1			
i		a	Flow at Topsia (1)	
		b	Flow at Ambedkar Bridge (2)	
		c	Flow at Bantala FFC (3)	
		d	Flow at Bamanghata FFC (4)	
		e	Flow at Karai Danga (16)	
		f	Depth at Chachchria	Flow at Chachchria (5)
ii			Input 1a -1e	
		f	Depth at Nalban	Flow at Nalban (13)
iii			Input 1a -1e	
		f	Depth at Dhali Bheri	Flow at Dhali Bheri
iv			Input 1a -1e,ii.f,iii.f	Flow at Ghusighata (17)
	2			
i		a - e	Flow at 1,2,3,4,16	
		f	Catchment Area of Chachchria Wetland	Flow at Chachchria
ii		a - e	Flow at 1,2,3,4,16	
		f	Catchment Area of Nalban Wetland	Flow at Nalban
iii		a - e	Flow at 1,2,3,4,16	
		f	Catchment Area of Dhalibheri Wetland	Flow at Dhali Bheri

Dhalibheri sewage ponds. In the second model, the catchment area of the ponds was also considered along with the inputs considered for the first model.

Table 3 depicts the values of the parameters used for the model. 70% of the total dataset was used as training, 15% was used for cross validation and 15% was used for testing. This breakdown is normal for the development of neural models. The genetic algorithm was applied to select the topology of all four networks. A population of 40 patterns was considered. Sixty generations were forced from those patterns, with a 90% crossover rate and 20% mutation capability (10% each for AQP2 and ACGD2). The models are named as AQP1 and AQP2 for the two networks trained in QP and ACGD1 and ACGD2 for the networks trained in CGD. The training was stopped whenever the MSE of the training subset dropped below 1%. All four networks were trained for 100 times with one lakh iterations per training. After the training, the average absolute error values achieved from the four networks were 0.0892, 0.0921, 0.0772 and 0.0872, respectively. The average absolute MSE values after training of these networks were 0.0900, 0.0970, 0.0099 and 0.0978, respectively. These results indicated that all networks had sufficiently “learned” the problem. The networks were tested with two patterns and the average MSE values were 0.79, 0.77, 0.50 and 0.65 for AQP1, AQP2, ACGD1 and ACGD2, respectively.

The average absolute error values were 0.87, 0.86, 0.75 and 0.85 for AQP1, AQP2, ACGD1 and ACGD2, respectively. The details of the networks are provided in Table 2. ACGD1 was selected as the network that performed best due to the least absolute and mean square error achieved from the network during the training and testing procedures. In order to compare the performance of the selected network with the regression model (equation 7), the MSE, r, C.E and STDDEV were calculated for both the computed and observed values.

The linear regression equation for the aforementioned condition was found to be:

$$y = \sum a_n x^m \quad (7)$$

where flow at the channel is considered to be x and flow at the sewage ponds is considered as y. Additionally, a_n is considered to be the equalization constant whose value is determined by the best fit approach.

These values helped to select the best performing network (Nash and Sutcliffe, 1970). The MSE values obtained were 0.63 and 6.948 units for the ANN and regression models, respectively. Network ACGD1 showed an improvement of 11.02 (MSE) times over the regression model. This demonstrates that ACGD1 was the best-fit algorithm for estimation when compared with the regression model. Estimated values from the ACGD1 network gave a high model efficiency of 98.8% against an efficiency of 67% for the regression model (Table 4). Again, the ACGD1 network was 1.47 times better than the regression model. The S.D for regression was found to be 0.095 times closer to zero and the S.D for ACGD1 was found to be 11.16 times closer to zero.

Hence, the ACGD1 model was 85% better than the regression model. Observed values from the ACGD1 were found to be 98%

Table 3. Summary of the architecture and internal parameters for the neuro-genetic model developed based on condition 1.

Network name	AQP1	AQP2	BCGD1	BCGD2
		Network topology		
Network type	Feed-forward fully connected network	Feed-forward fully connected network	Feed-forward fully connected network	Feed-forward fully connected network
Number of inputs	10	10	10	10
Number of hidden layers	2	1	2	2
Hidden units in the 1st hidden layer	6	1	6	6
Hidden units in the 2nd hidden layer	8	0	8	8
Number of outputs	7	7	7	7
Training algorithm	Quick Propagation	Quick Propagation	Conjugate gradient descent	Conjugate gradient descent
		Stop training conditions		
The value that the MSE on training subset must drop below	0.01	0.01	0.01	0.01
The maximum allowed number of iterations	100000	100000	100000	100000
Training stop reason	Maximum iteration was reached	Maximum iteration was reached	Desired error level was achieved	Maximum iteration was reached
		Training results		
Average MSE (training)	0.09	0.097	0.00993	0.0978
Average MSE (testing)	0.87	0.86	0.75	0.85
Average absolute error (training)	0.08921	0.0921	0.07721	0.08721
Average absolute error (testing)	0.79	0.77	0.5	0.65

related to the target values, whereas the regression model were found to be only 3% less related to the target values. Thus, according to the performance validating criteria, ACGD1 was more capable than the re-gression model for the estimation of the output parameters. The second model was prepared with the parameters selected according to the objectives described in condition 2. The models for this condition were built to be identical to the first model for the four networks (named BQP1 and BQP2 for the two networks trained in QP and BCGD1 and BCGD2 for the networks trained in CGD). The average absolute error values were 0.09, 0.097, 0.078 and 0.088 for BQP1, BQP2, BCGD1 and BCGD2, respectively (Table 5). The average absolute MSE values from the training of these networks were 0.87 (BQP1), 0.86 (BQP2), 0.75 (QP) and 0.85 (BCGD1), (Table 3) which indicated that all networks had sufficiently learned the present problem. The average MSE values for the testing dataset were found to be 0.8, 0.78, 0.6 and 0.66 for BQP1, BQP2, BCGD1 and BCGD2, respectively. The average absolute error values were 0.77, 0.76, 0.55 and 0.65 for BQP1, BQP2, BCGD1 and BCGD2, respectively. The details of the networks are given in Table 5. The network of BCGD1 was selected as the best performing network due to the least absolute and mean square error achieved from this network during the training and testing procedures.

The MSE value obtained for ANN models was 0.63 and the MSE for regression models was 1.53. The BCGD1 network showed an improvement of 2.43 times the regression model. This reveals that BCGD1 was the best-fit algorithm for the estimation. The estimated values from BCGD1 were closer to zero than target values by 0.095 units and the estimated values from the regression model

Table 4. Summary of the optimum ANN model's architecture and ANN internal parameters.

Parameters	MSE	R	C.E	S.D
ACGD1	0.63	0.98	0.988	0.095
Regression	6.948	0.95	0.67	11.16

Table 5. Summary of the architecture and internal parameters for the neuro-genetic model developed based on Condition 2.

Network name	AQP1	AQP2	BCGD1	BCGD2
Network topology				
Network type	Feed-forward fully connected network	Feed-forward fully connected network	Feed-forward fully connected network	Feed-forward fully connected network
Number of inputs	3	3	3	3
Number of hidden layers	2	1	2	2
Hidden units in the 1st hidden layer	6	1	6	6
Hidden units in the 2nd hidden layer	8	0	8	8
Number of outputs	9	9	9	9
Training algorithm	Quick propagation	Quick propagation	Conjugate gradient descent	Conjugate gradient descent
Stop training conditions				
The value that the MSE on training subset must drop below	0.01	0.01	0.01	0.01
The maximum allowed number of iterations	100000	100000	100000	100000
Training stop reason	Maximum iteration was reached	Maximum iteration was reached	Desired error level was achieved	Maximum iteration was reached
Training results				
Average MSE (training)	0.0945	0.0966	0.00993	0.0978
Average MSE (testing)	0.8	0.78	0.6	0.66
Average absolute error (training)	0.09	0.097	0.078	0.088
Average absolute error (testing)	0.77	0.76	0.55	0.65

were closer to zero by 11.16 units. The BCGD1 network was 11.16 times closer than the values predicted by the regression model. The estimated values from BCGD1 gave a high model efficiency of 97.8%, which is 1.57 times more efficient than the regression model (Table 6). Observed values from the BCGD1 were found to be 98.5% related to the target values, whereas observed values of the regression model were found to be 95% related to the target values. Hence, BCGD1 was 3.5% more related than the regression model. According to the performance validating criteria, BCGD1 was selected over the regression model for better estimation accuracy.

RESULTS AND DISCUSSION

A major part of Kolkata City sewage is upgraded in an ecologically balanced treatment system through unique pisciculture. At present, the average discharge of city sewage in DWF is approximately 1000 MLD and existing pisciculture area is 3898.70 ha. Kolkata Municipal Corporation (KMC) has taken up augmentation of sewerage system, as well as laying of sewerage network in unsewered areas of the city under Kolkata environmental improvement project (KEIP). The sewerage development programme will generate increased quantum of sewage which will be discharged in EKW. In order to maintain ecologically balanced waste-water management system in EKW, more pisciculture units need to be developed so as to restrict the relevant parameters of the wastewater below maximum permissible limit at Ghusighata. Recent field surveys showed that 8,500 people are directly engaged in sewage-fed fisheries, of which about 90% are from local villages within the EKW, while the others mainly coming from adjoining areas of Districts 24-Parganas (North) and 24-Parganas (South), Midnapore and some from neighbouring states. Fish farming presents opportunities for various types of specialized labour, including security services, harvesting

Table 6. Summary of optimum ANN model's architecture and ANN internal parameters.

Parameter	MSE (%)	R	C.E	S.D
BCGD1	0.63	0.98	0.978	0.095
Regression	1.53	0.95	0.67	11.16

work, loading, unloading, packing and distribution of fish, and as a consequence such opportunities often attract migrant labourers from other districts and states (Bunting et al., 2005).

In general, however, traditional economic activities, namely sewage-fed agriculture and fish farming, primarily involve the inhabitants of the EKW. The main stake-holders are the fish farmers, labourers engaged in fish farming and agriculture, night guards and carriers. According to the inhabitants, both agriculture and fish farming often suffer from a lack of wastewater. Over 50 communities in the EKW were interviewed. All of these communities stated the same desires – better access to sewage flows to enhance fish production, improve sewage quality which had deteriorated because of the lack of flows in recent years (Awareness Generation and Community Mobilization in East Kolkata Wetlands Area, Centre for Environmental Management and Participation Development, 2004). These comments are supported by the conclusions of Bunting et al. (2005) found later in this document.

The ACGD1 and BCGD1 models selected were used during the study to predict the impact of the excess load on pisciculture units. In the models, an exiting flow in the DWF was considered to be 1000 MLD with an area of 3898.7 ha. This prediction was made using the model analysis for enhanced flow of 1100 and 1200 MLD in the DWF. Two different loops were considered in the model since the study was concentrated in three fishery cooperatives in the EKW. The model prediction indicated that the depth of the water in fish ponds could be increased between 76.2 to 101.6 mm. This increase would allow an increase of sewage flow by 15.21 to 19.12%. If the input flow could be enhanced to 1100 MLD, then the depth of the pond water could be further increased by 18.53 to 39.54%. Similarly, if the flow of sewage in the DWF could be increased to 1200 MLD, then a further increase in the depth of the fish ponds by 58.51 to 69.34 mm would be possible, resulting in the potential to accommodate 32.25 to 88.9% more sewage in the fish ponds. According to the prediction results from the ACGD1, an area of 5000 ha could be accommodated 1200 MLD of sewage flow. In such a case, the maximum depth in the fish ponds would be increased up to 106 mm.

Conclusions

The present pond system in the EKW is a highly efficient, low cost, low carbon emission footprint system for treating wastewater from a major urban centre. This treatment process also supports a large rural population involved in sewage-fed fish farming and agriculture. The present study used a neural network to estimate the impact of enhanced flow on a cluster of wetlands connected to a DWF channel. Two neural network models were prepared. The first model was prepared to estimate the flow in three fisheries loops (DWF to fishery networks), with varied depth to keep the area constant. The second model was prepared to predict the flow in three different loops (DWF to fishery networks) that varied in both depth and total area of the ponds. From the results of the two models, it can be concluded that if the total area of the wetlands is increased up to 5000 ha, resulting in a depth of 106 mm, then the wetlands will be able to accommodate an enhanced flow of 1200 MLD. The augmentation of Kolkata drainage system undertaken under KEIP would result in approximately 20% increase of wastewater from the city.

The present sewage fed fisheries would be capable of utilizing the enhanced waste water with a little modifi-cation in the ponds configuration, such as increase in depth up to 106 mm from the existing depth and it can be treated in these ponds to meet the discharge criteria for inland surface water. The Ramsar listing of the EKW is based upon the continued wise use of the area. This is best achieved by enhancing the fishery and associated agriculture, supporting the sustainable livelihoods of the community. The EKW provides about 150 tons of fresh vegetables daily, as well as some 10,500 tons of table fish per year, the latter providing livelihoods for about 50,000 people directly including fishery, agriculture and waste management and as many again indirectly. The fish ponds are mostly operated by worker cooperatives, in some cases in legal associations and in others in cooperative groups whose tenurial rights are under legal challenge. The biodiversity values (that is mammals, reptiles, fish and bird species) of the EKW will also be preserved as the additional wastewater will be treated in the existing ponds. The pond system has additional capacity to treat more wastewater based on a number of parameters tested in this study. There is a high probability that fish production will increase because of the additional sewage load.

However, this additional loading should be carefully supported by a decent channel desilting program. This increased flow provides additional fertilizer to the fish ponds of the EKW. The fish ponds operate very successfully at present in producing a treated effluent with low BOD, low bacterial numbers, reduced ammonia concentrations and high dissolved oxygen concentrations. However, total nitrogen concentrations are relatively low for optimal fish production. Therefore, any additional inputs of nitrogen are likely to be beneficial, with loads up to 4 kg/ha/day (Mara et al., 1993). At present, this loading is substantially less (< 2 kg/ha/day). Additional sewage has the potential to supply a further 0.5 to 1 kg/ha/day of nitrogen (Jadavpur University, 2007). The additional sewage flow is predicted to meet WHO guidelines for wastewater-fed aquaculture and irrigation for agriculture.

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