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Prediction of chemical oxygen demand of primary clarifier effluent in wastewater treatment plant

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Abstract—*The industrial effluent treatment plant or waste water treatment plant (WWTP) is a facility to remove pollutants from wastewater. Generally, in WWTP chemical oxygen demand, pH, total suspended solids, influent flow rate, biochemical oxygen demand, total dissolved solids, ammoniacal nitrogen etc. are observed to maintain their values as per the government law. In this paper Artificial neural network is applied to predict chemical oxygen demand present in effluent of primary clarifier. Primary clarifier is the physical subsystem of WWTP to remove suspended solids from the influent wastewater. Three COD prediction models are developed using Levenberg-Marquardt (LM), One Step Secant (OSS), and BFGS quasi newton algorithm. The R-squared values obtained for LM, BFGS and OSS are 0.99, 0.98 and 0.89 respectively. The root mean square error for LM, BFGS and OSS are 190.1, 209.4 and 573.5 respectively. As per the results obtained the Levenberg-Marquardt model predict better COD as compared to the COD predicted by BFGS and OSS models.*

Keywords : *Wastewater, Neural network.*

INTRODUCTION

1.1 Waste water treatment plant

The industrial effluent treatment plant or the wastewater treatment plant is a facility in which physical, chemical and biological processes are used to remove pollutants from industrial wastewater. The measurement of various pollutants is carried out by experimental analysis or online instrumentation. The experimental analysis procedure consumes much time while online instrumentation is expensive. For the estimation or prediction of such pollutants various data driven techniques are used termed as soft sensors. These techniques comprise statistical models or artificial neural network-based models [1].

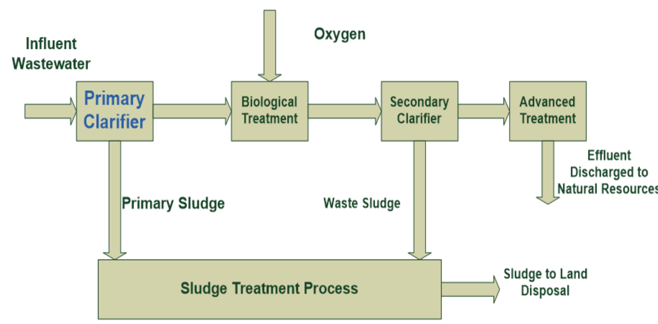

Fig. 1 Block diagram of WWTP

As shown in Figure 1 the primary clarifier removes solid particles with gravitation force. The clear water exits from the top of the equipment and sludge is collected at the bottom of the equipment. The collected sludge is diverted to sludge treatment process. The clear water from the primary clarifier is entered in the biological treatment where air is added into wastewater to allow aerobic biodegradation of pollutant components. The formed flocs can easily settle out. After the biological process the next process is secondary clarification. Secondary clarifiers are used to remove the settleable suspended solids created in the biological treatment process.

For the monitoring and control of whole plant or each subsystems the measurement of pollutants at input and output side of each sub system is required. The measurements of such pollutants require online instrumentation or experimental analysis. Online instrumentation is costly and experimental analysis requires much time to get measurement. In this situation model-based sensors or virtual sensors or soft sensors are solution. These sensors are based on statistical or artificial intelligence techniques.

1.2 Artificial Neural Network

Artificial neural networks (ANN) are machine learning techniques that are designed to imitate human brain. ANNs are used to find solutions or models for prediction, optimization and system control. The commonly used artificial intelligence techniques are [2]: Adaptive network- based fuzzy inference system, feedforward neural network, radial basis function network, random forest, recurrent neural network, Self-organizing map. All these techniques in literature are mainly used for whole plant or biological process like ASP.

Haimi et. el[2]. presented statistics of various data driven techniques used for the prediction of pollutants for biological wastewater treatment plant.

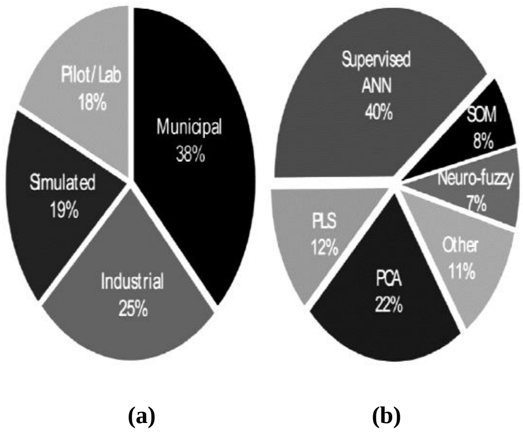

Fig. 2. Wastewater treatment process types and methods for the soft sensor design [Haimi et al., 2013]. [2]

As shown in Fig.1(a) various statistical and artificial intelligence methods have been adopted for pilot/lab scale (18%), Municipal (38%), Simulated (19%) and industrial (25%). The methods adopted for prediction of various pollutants are supervised ANN (40%), Self-organizing map (8%), Neuro-fuzzy (7%), Principal component analysis (22%), Partial least square (12%), Neuro-Fuzzy (7%) and others (11%).

In this study primary clarifier of WWTP is considered. The input variables are pH, total organic carbon (TOC), chemical oxygen demand (COD), BOD (Biochemical Oxygen Demand), total dissolved solids (TDS), ammoniacal nitrogen (NH3-N). The output variable is COD. The COD models are developed using artificial neural network tool on MATLAB^{TM} platform.

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METHODS

2.1 Levenberg- Marquardt Algorithm

To solve nonlinear least squares problems, the Levenberg-Marquardt (LM) Algorithm is used [3][4]. This curve-fitting method is a hybrid of two others: gradient descent and Gauss-Newton.

Both the Gradient Descent and Gauss-Newton algorithms are iterative, which means they use a series of calculations (based on x-value guesses) to find a solution. The gradient descent method differs in that the solution is updated at each iteration by selecting values that reduce the function value. More specifically, the sum of the squared errors is reduced by moving toward the steepest descent direction. The Levenberg-Marquardt Algorithm selects either gradient descent or Newton’s gradient and updates the solution at each iteration**.**

2.2 BFGS Quasi Newton Algorithm

Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm is an iterative method for solving unconstrained nonlinear optimization problems. Like the related Davidon–Fletcher–Powell method, BFGS determines the descent direction by preconditioning the gradient with curvature information [5]. Like steepest descent, quasi-Newton methods require only the gradient of the objective function to be supplied at each iteration. They build a model of the objective function that is good enough to produce superlinear convergence by measuring changes in gradients. The difference between the steepest descent and the easiest problems is dramatic. Furthermore, because second derivatives are not required, quasi-Newton methods can be more efficient than Newton's method. Optimization software libraries now include a wide range of quasi-Newton algorithms for solving unconstrained, constrained, and large-scale optimization problems.

(BFGS) algorithm is an iterative method for solving unconstrained nonlinear optimization problems that belongs to the Quasi-Newton family [6][7]. By preconditioning the gradient with curvature information, BFGS determines the descent direction by preconditioning the gradient with curvature information.

2.3 One Step Secant Algorithm

Because the BFGS algorithm necessitates more storage and computation in each iteration than the conjugate gradient algorithms, a secant approximation with lower storage and computation requirements is required [8,9]. The one step secant (OSS) method aims to bridge the gap between conjugate gradient and quasi-Newton (secant) algorithms. This algorithm does not store the entire Hessian matrix; instead, it assumes that the previous Hessian was the identity matrix at each iteration. This has the added benefit of allowing the new search direction to be calculated without the need for a matrix inverse, describes the one-step secant method. Compared to the BFGS algorithm, this algorithm requires less storage and computation per epoch. It necessitates a little more storage and computation per epoch than the conjugate gradient algorithms. It can be thought of as a middle ground between full quasi-Newton algorithms and conjugate gradient algorithms.

RESULTS

Fig. 3 shows regression plot for Levenberg- Marquardt model. The R values for training, validation, testing and all obtained are 0.82, 0.71, 0.73 and 0.79 respectively. Fig. 4 represents measured vs predicted values of COD.

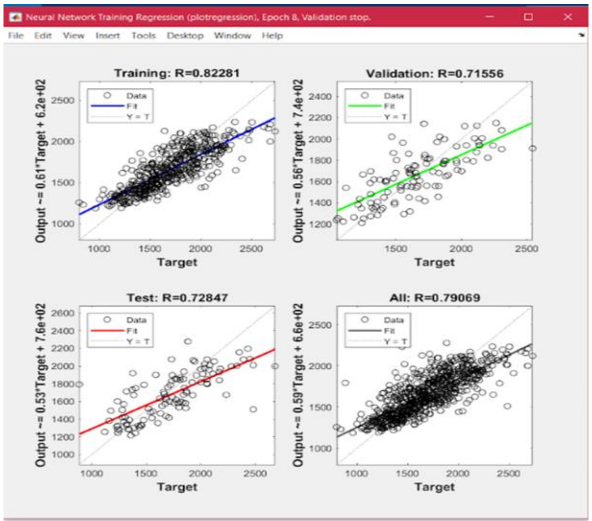

Fig. 3 Levenberg- Marquardt regression plot

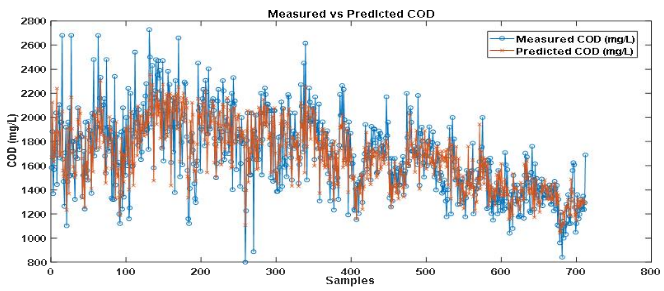

Fig.4 Measured vs predicted COD, (Levenberg- Marquardt model)

Fig. 5 shows regression plot for BFGS model. The R values for training, validation, testing and all obtained are 0.76, 0.80, 0.81 and 0.78 respectively. Fig. 6 represents measured vs predicted values of COD for BFGS model.

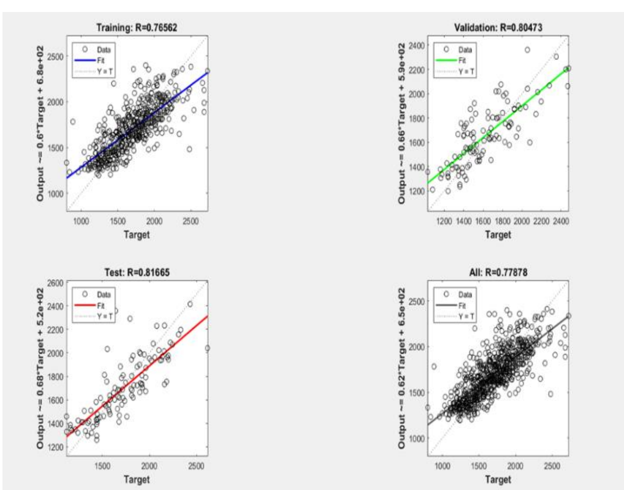

Fig. 5 BFGS regression plot

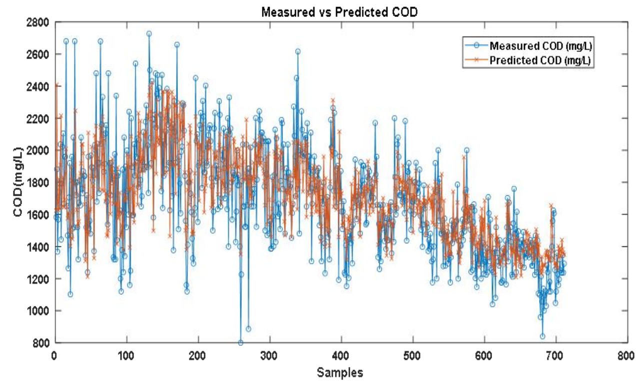

Fig. 6 Measured vs predicted COD (BFGS model)

Fig. 7 shows regression plot for BFGS model. The R values for training, validation, testing and all obtained are 0.33, 0.41, 0.15 and 0.32 respectively. Fig. 8 represents measured vs predicted values of COD for One Step Secant model.

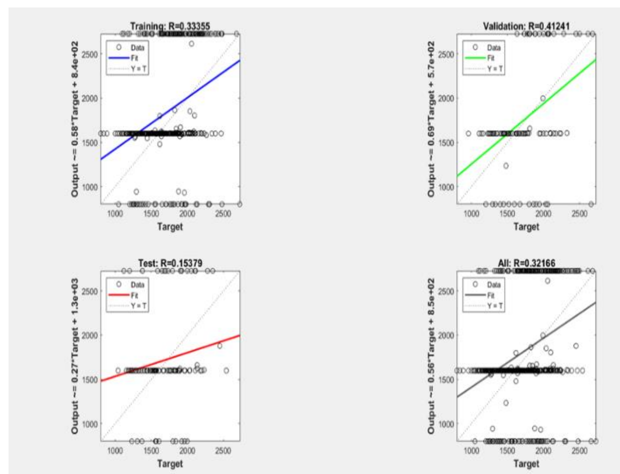

Fig. 7 One Step Secant model regression plot

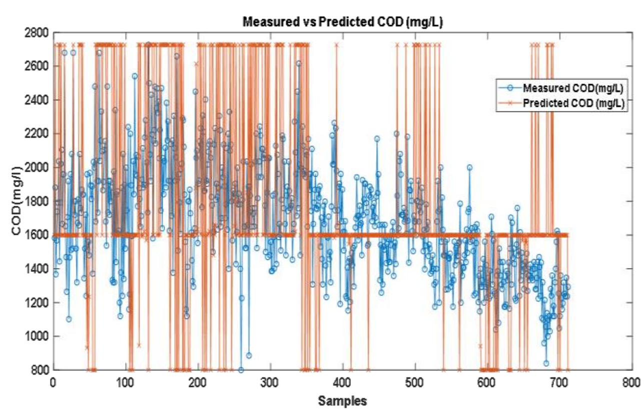

Fig. 8 Measured vs predicted COD (One Step Secant model)

The performance of the developed COD models is evaluated by root mean square error (RMSE) and R2 values. As shown in Table 1 the R2 values obtained by Levenberg- Marquardt, BFGS and One Step Secant models are 0.99, 0.98 and 0.89 respectively. The RMSE for Levenberg- Marquardt, BFGS and One Step Secant models are 190.1, 209.4 and 573.5 respectively. As per the results obtained the Levenberg-Marquardt model predicts COD better as compared to BFGS and One Step Secant models.

Table 1. Comparison of Levenberg- Marquardt, BFGS and One Step Secant models for COD prediction.

Model	R^2	RMSE
Levenberg Marquardt	0.99	190.1
BFGS Quasi Newton	0.98	209.4
One Step Secant	0.89	573.5

CONCLUSION

In wastewater treatment plants it is important to measure the system variables for monitoring and control purpose. The model-based sensors play an important role for monitoring the process. In this study three artificial neural network models have been developed for the prediction of COD present in effluent of primary clarifier. Among the three models Levenberg- Marquardt model predicts better than the BFGS and One Step Secant models in terms of R2 and RMSE. The predicted values can be used for decisive control action. The developed models can be integrated with control action for automatic control.

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