Rapid prediction of effluent biochemical oxygen demand for improved environmental control

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ABSTRACT

Millions of dollars are spent annually by the pulp and paper industry developing and operating wastewater treatment systems and modifying production to achieve the water emissions limits set by environmental regulatory agencies. This paper presents recent developments in predicting and controlling one of the most critical and problematic mill water effluent parameters to measure—biochemical oxygen demand (BOD)—using an artificial neural network system installed in an integrated pulp and paper mill.

BOD emission is one of the most important of the regulated parameters since it impacts dissolved oxygen (DO) levels in the receiving water. Higher BOD increases the natural level of microorganism activity, which lowers dissolved oxygen levels. Fish and other higher life forms can suffer from lack of oxygen in extreme cases. Because of its importance to the health of the receiving water, BOD emission is tightly regulated. One major difficulty in monitoring and controlling BOD stems from the long delay (5 days) in obtaining results by the standard test (1). *This delay makes it difficult for the pulp and paper and other regulated industries to respond to variations in BOD in a timely manner. To prevent permit excursions, a facility may curtail production and, if unsuccessful in meeting the limit, may be fined thousands of dollars per day. To help address this problem, we have developed and implemented a method to rapidly predict BOD with excellent accuracy. This allows the mill to take timely and appropriate remedial actions to prevent permit violations and protect the environment.*

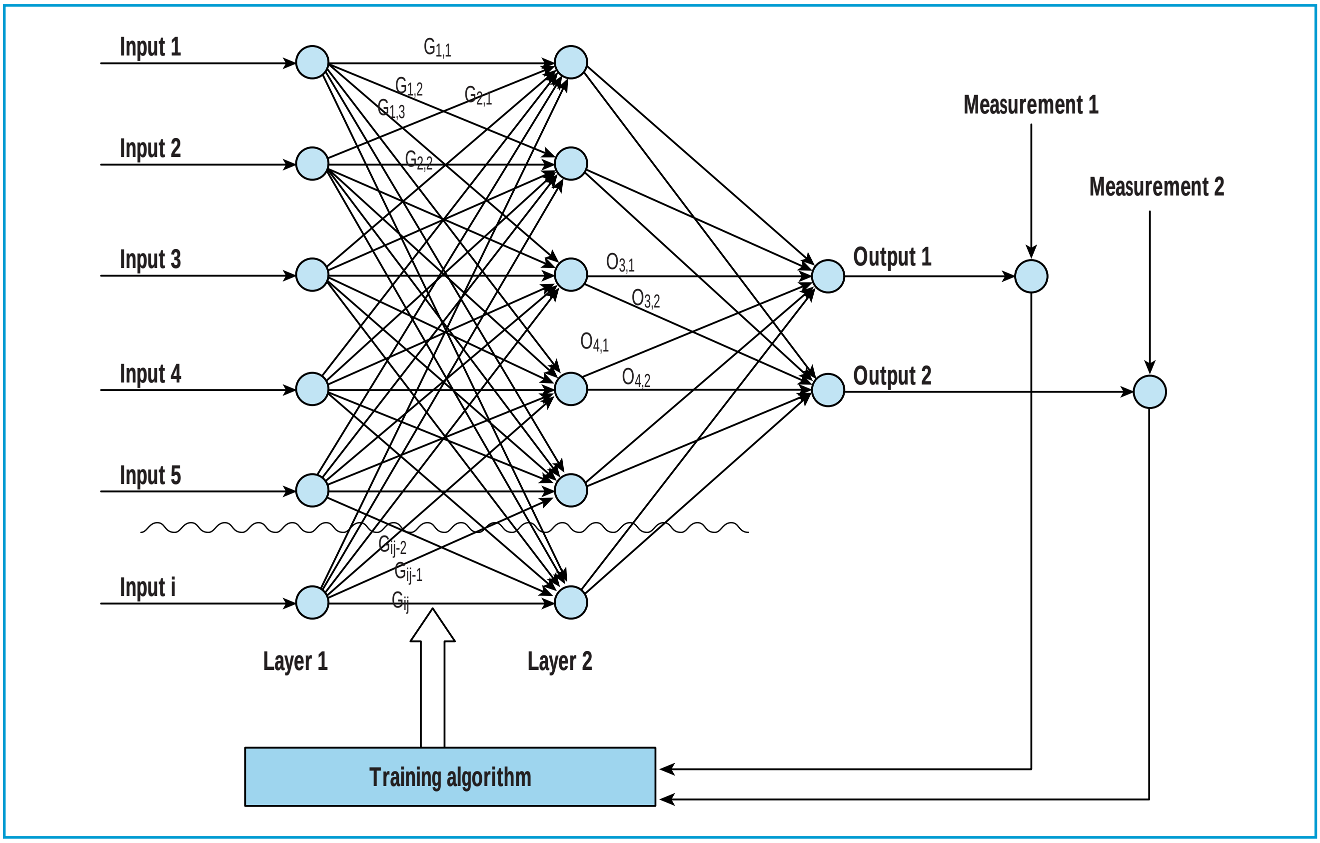
Application:
On-line prediction of mill effluent BOD, using a neural network model, was implemented in a waste treatment plant.

TIMELY KNOWLEDGE OF THE impact of changes in process variables on process performance is critical for profitable and efficient operations. Due to the large existing and growing database of production information, many researchers have attempted to build mathematical models relating quality and performance factors to measured production parameters (2).These prediction models are especially useful when there is a long delay in the measurement. One such mathematical tool is the neural network model, which has received heightened interest and attention in recent years (3). The neural network methodology uses artificial intelligence methods to build nonlinear multivariable models based on large amounts of data. These techniques are not based on fundamental physical or chemical principles and must be combined with practical insight to be effective.

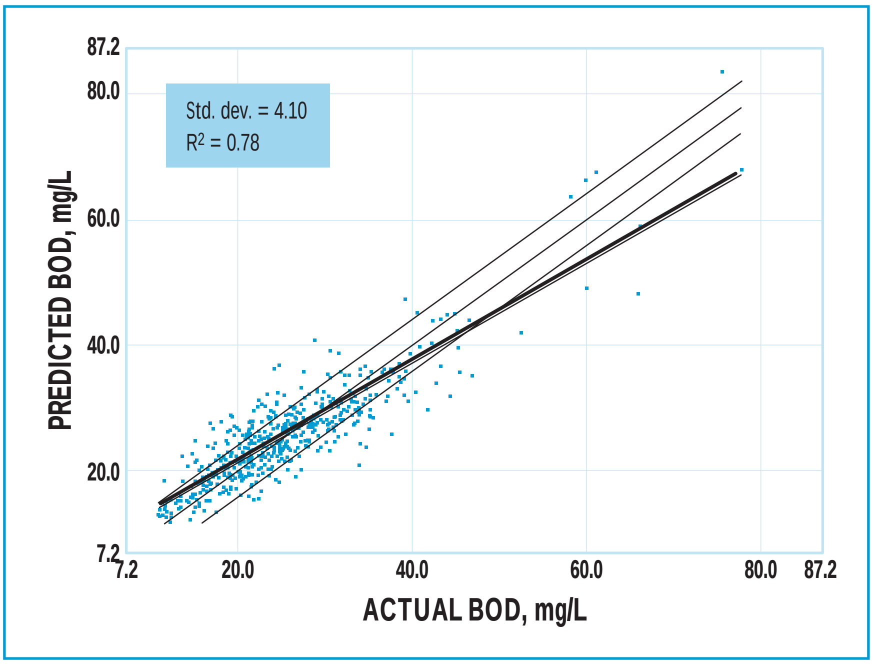
This paper demonstrates how the neural network approach was successfully used to build a predictive model of the biochemical oxygen demand (BOD) for a waste treatment plant effluent stream. The standard BOD test consists of completely filling an airtight bottle of a specified size with the test fluid and incubating it at a specified temperature for 5 days *(1)*. BOD is calculated as the difference between initial and final dissolved oxygen and appropriate sample dilution factors. Other researchers have evaluated different methods for rapid BOD measurement *(4–6)*, but these methods have generally not performed well for industrial effluents. The predictive modeling approach described in this paper allowed a pulp and paper mill to respond faster to process disturbances and to improve control of effluent BOD. Better control of BOD should, in turn, enhance environmental performance.

A mathematical model that predicts the BOD of mill effluents from operating parameters has been developed based on empirical analysis of relationships among more than 100 mill production parameters and mill BOD values during the past 2 years. The final model predicts BOD from 11 input parameters, which are entered each day by plant operators. The model, which runs on a personal computer and is linked to the mill process information system, was put on-line in March 1998. Significant software improvements were made in July 1998 to allow greater flexibility, reliability, and ease of use.

Neural network technology is a powerful tool for building dynamic and steady-state models for prediction and/or control purposes. Neural networks are especially useful when fundamental first-order principles cannot be easily used to model the process and when a large amount of historical data is available. Artificial neural networks can be used to build and train a model based on nonlinear and multivariable pattern-recognition methods. Data analysis and model development were performed using a commercial neural network software program *(7)*. Building large models for nonlinear and complex



1. Structure of the artificial neural network model



2. Predicted vs. actual BOD for Model B training set

applications, such as predicting mill effluent BOD, is now practical due to significant improvements in the capabilities of neural network software, lower computing costs, and the availability of adequate historical production and manufacturing data.

Artificial neural networks are able to learn mappings between large sets of input and output data. These mappings are achieved by training the network using sets of input–output pairs. On being presented with an input, the network compares the corresponding measured output with its own output and uses the error to adjust its weights and biases (**Fig. 1**). Note that the artificial neural network shown in Fig. 1 has *i* input variables, two output variables, and one intermediate (or hidden) layer. Each node in the network receives several inputs from the preceding layer, multiplies each by the appropriate gain ($G_{i,j}$), adds a bias coefficient, and sends the output to the next layer. The optimum gains and bias coefficients are determined using a training algorithm, such as back-propagation *(2)*, that minimizes the mean-squared error between the measured and calculated outputs. A more general dis-

Rank no.	Input name	Sign of average sens. coefficient
1	Final effluent COD	+
2	Sludge bed depth no. 2	–
3	Oxygen uptake out	+
4	Effluent suspended solids	+
5	Sludge bed depth no. 1	+
6	Stalked protozoan counts	–
7	Influent flow	–
8	Stream 4 acid pH	–
9	Bleach room composite pH	–
10	Bleach room total flow	–
11	SO_2 scrubber flow	–
12	Influent suspended solids, ppm	+
13	Primary effluent suspended solids	+
14	Flow to river	+
15	COD in	+
16	Total influent pH	–
17	Final effluent temperature	+
18	Total paper mill flow	–
19	Aeration airflow	+
20	Final effluent pH	+
21	Final effluent color	–
22	WTP* effluent flow	+
23	Pulp mill flow	–
24	SO_2 scrubber pH	+
25	Lime usage	+
26	Outfall suspended solids	+
27	Waste flow	+
28	Stream 5 pH	–
29	Recovery stream flow	–
30	Influent suspended solids, lb/day	+

*Waste treatment plant

I. Model A input variables and their sensitivity coefficients

Rank no.	Input name	Sign of average sens. coefficient
1	COD out	+
2	Effluent suspended solids [a]	+
3	Effluent suspended solids [b]	+
4	Oxygen uptake out	+
5	WTP[c] effluent flow	+
6	Influent flow	–
7	Stalked protozoan counts	–
8	SO_2 scrubber flow	–
9	Influent suspended solids	+
10	Sludge bed depth no. 2	–
11	Final effluent color	–

aComposite of 36 daily samples
bAverage of 6 daily samples
cWaste treatment plant

II. Model B input variables and their sensitivity coefficients

cussion on artificial neural networks and training algorithms may be found in the literature *(8, 9).*

MODEL DESCRIPTION

Averaged daily data for 124 waste treatment process parameters over the past 2 years were collected and used to build and train alternative models for predicting BOD. Process parameters include suspended solids, chemical oxygen demand (COD), color, pH, and flow rates for all the streams in and out of the waste treatment plant. Neural network models were developed with the whole data set and with smaller subsets to evaluate the individual and combined effects of the inputs. Developing practical and useful neural network applications involves an empirical technique; good engineering judgement and experience are important in selecting parameters and ensuring good data.

A neural net can have an unlimited number of inputs and outputs; however, inputs that are strongly correlated with each other may cause the model to focus on one input and ignore the others. Also, occasional sensor failures adversely affect model performance. Approximately 20 models were built and compared for accuracy and system reliability. Two such models will be presented and compared in this paper.

Model A

Model A uses 30 inputs. After the inputs were selected and the model trained, the inputs were ranked in terms of the magnitude of their effect (sensitivity) on the effluent BOD (see **Table I**). The inputs were ranked by the average of the absolute value of their sensitivity coefficients. The sign of the average sensitivity coefficient (third column in Table I) indicates whether an increase in the input variable causes an increase in BOD (positive sign) or a decrease in BOD (negative sign).

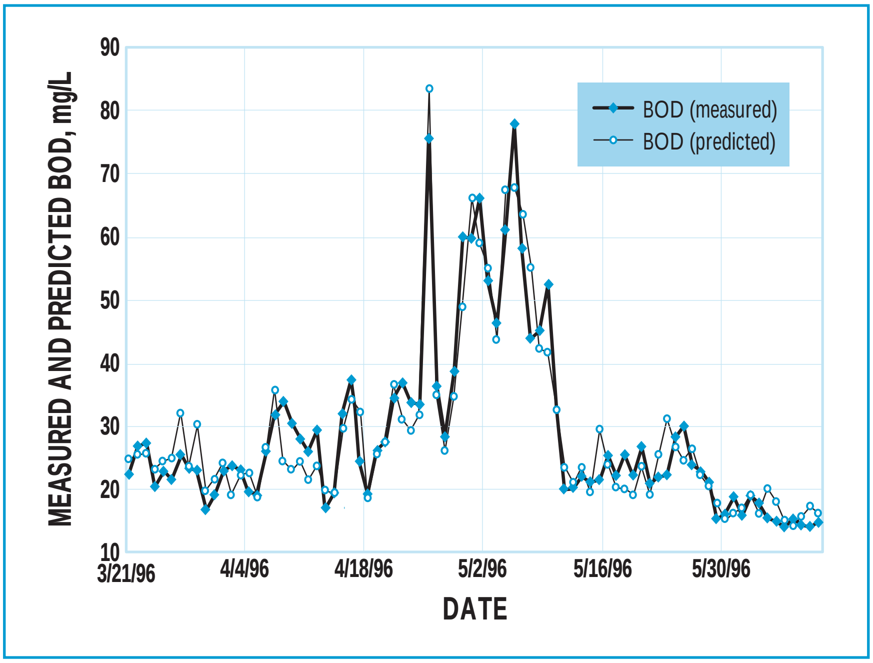
Model A, with 30 input variables, is the most accurate (R^2=0.79) of all the models tested. A drawback is that it uses many variables, which can cause reliability problems due to sensor failures *(3)*. To reduce the number of inputs, the variables with the highest sensitivity coefficients from different models were combined, and the model was retrained with fewer inputs. Note that selecting the right inputs is an iterative process that requires practical experience and engineering judgment.

Model B

The second model, Model B, which was implemented on-line as a virtual sensor, uses 11 inputs, which are listed and ranked in **Table II.** No single variable has a dominant effect on biochemical oxygen demand in this model; this demonstrates the need for multivariable modeling.

Figure 2 shows a plot of predicted vs. actual BOD for the training set, using Model B with 11 inputs. A perfect model would have a slope of 1, a standard deviation of 0, and an R^2 value of 1. As shown in Fig. 2, Model B has an R^2 value of 0.78, indicating good correlation of the data.

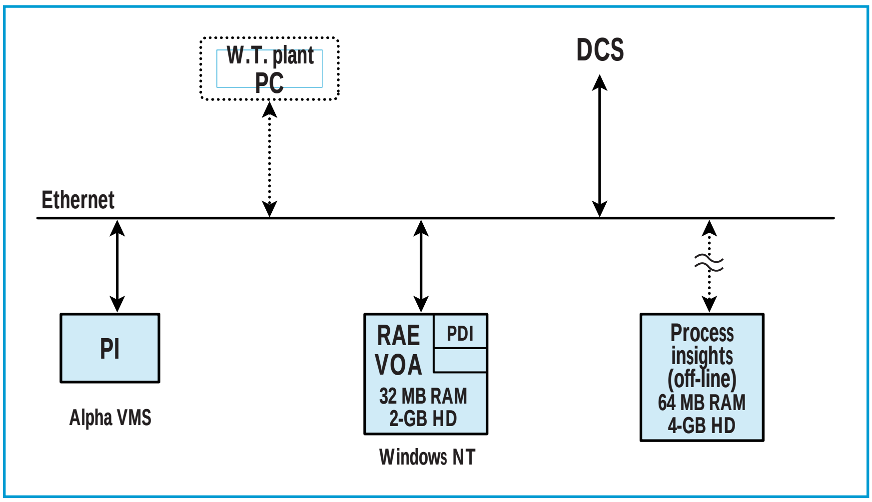
Comparison of the slope, R^2, and standard deviation of the error indicates that Models A and B are essentially equivalent (see **Table III**). Model B is preferred because it



3. Measured and predicted BOD for Model B training set

Parameter	Model A	Model B
Slope	0.797	0.792
R^2	0.797	0.784
Std. dev.	4.279	4.186
Inputs	30	11

III. Performance measures for Models A and B



4. Structure for the BOD model residing on a Windows NT personal computer

uses fewer inputs and is therefore more resistant to sensor failures or malfunctions. Model B was chosen for our first on-line implementation of the BOD predictor.

Figure 3 shows the measured and predicted BOD values for a portion of the data used in training the model. The predicted BOD represents the measured BOD well, including the high excursions when BOD exceeded 40 mg/L. It is during these excursions that the model is most useful since it provides the plant operator with an early warning system so that he or she can make the appropriate response.

The predicted BOD values shown in Fig. 3 demonstrate good agreement with measured values; however, the predicted values were calculated with data that were used in training the model. The final test for the value of this model involves evaluating its performance with new data that were not used in training the model. To do that, the model was implemented and tested on-line.

IMPLEMENTATION ISSUES

The BOD prediction model was implemented using a Pentium-based personal computer (PC) running Windows NT; the PC was connected to the mill's data process information (PI) system. A Runtime Application Engine (RAE) running on a PC automatically reads input data from PI and writes the predicted BOD value to the PI system. **Figure 4** shows the computer network structure used for communication between the BOD virtual on-line analyzer (VOA) and the mill's process information (PI) system.

The input variables required for the BOD model are entered manually by the operator. The system was configured to allow flexible sampling time so that the operator can enter data and request a BOD prediction at any time. During process upsets, the operator can sample more frequently and receive the guidance and benefits of the predictive model as desired.

Figure 5 shows actual and predicted BOD values for 22 days using recent data that were not used in training the model. The model predicts actual BOD values fairly well, plus it has the benefit of providing results 5 days ahead of results from the actual BOD test, as shown in Fig. 5.

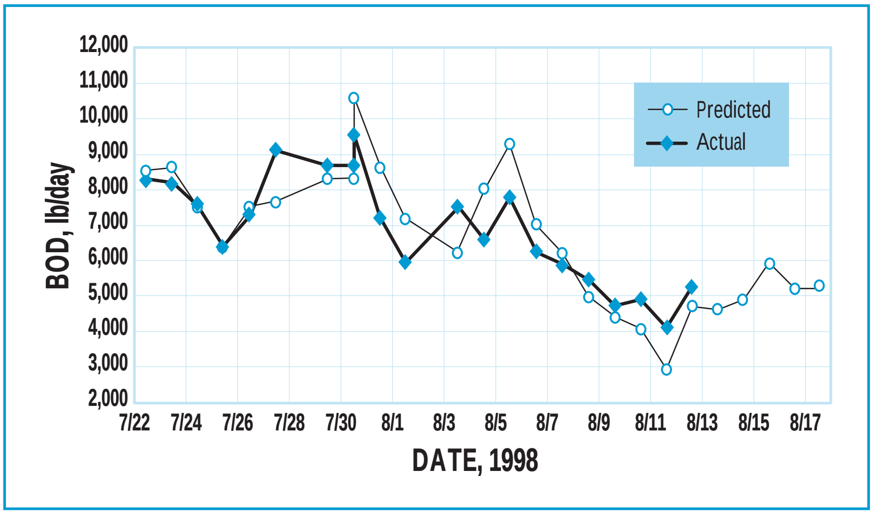
BIAS FEEDBACK ALGORITHM

After the BOD predictor was implemented, it ran for several weeks with no problem. However, beginning approximately August 15, a persistent error (bias) was noticed between the actual and the predicted values, as shown in **Fig. 6.** Before August 15, the predicted BOD correlated very well with the measured BOD, including excursions in BOD. After August 15, a significant and steady error between the actual and predicted BOD values was noticeable, although the trend is still the same.

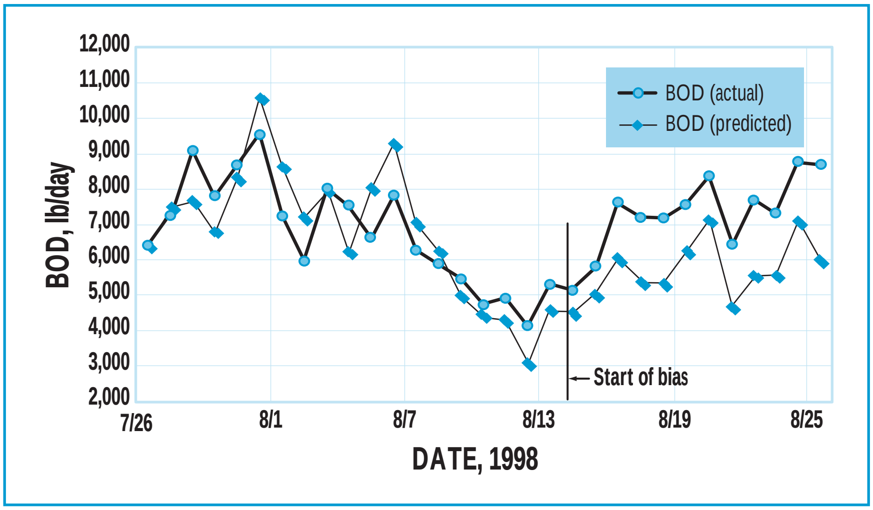
It was difficult to determine the cause of this bias. It could have been caused by unmeasured changes in the pulp mill or in the waste treatment plant operations, or by changes in the production schedule. No practical model can include all the potential inputs and variables affecting the waste treatment plant operation. Some of these variables are not measured or, if they are, they represent an aggregate measure with long time delays and uncertainties.

Since the neural network model is based on empirical data rather than first principles, it cannot predict responses to situations not represented in the original training set. Furthermore, the mill regularly makes modifications to improve the operation of individual elements in the overall process. Therefore, errors between the model prediction and the plant performance are bound to develop over time. Two ways to deal with these errors have been utilized in this work. The first is to retrain the model on a regular basis, and the second is to implement an algorithm that continually corrects for a persistent error (bias) between the model predictions and the plant data. It is also possible to allow the model to be continuously and automatically retrained with plant data; however, this technology has not been adequately tested.

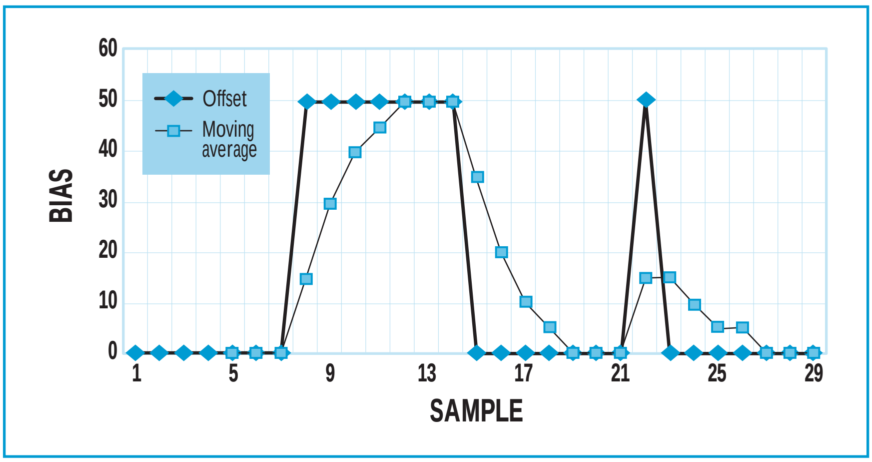
To handle short-term changes in manufacturing or operation procedures and to make the model more robust to unmodeled or unmeasured variations, a "bias feedback" algorithm was implemented. This algorithm consists of taking the average error between the actual and the predicted BOD for the last five available data



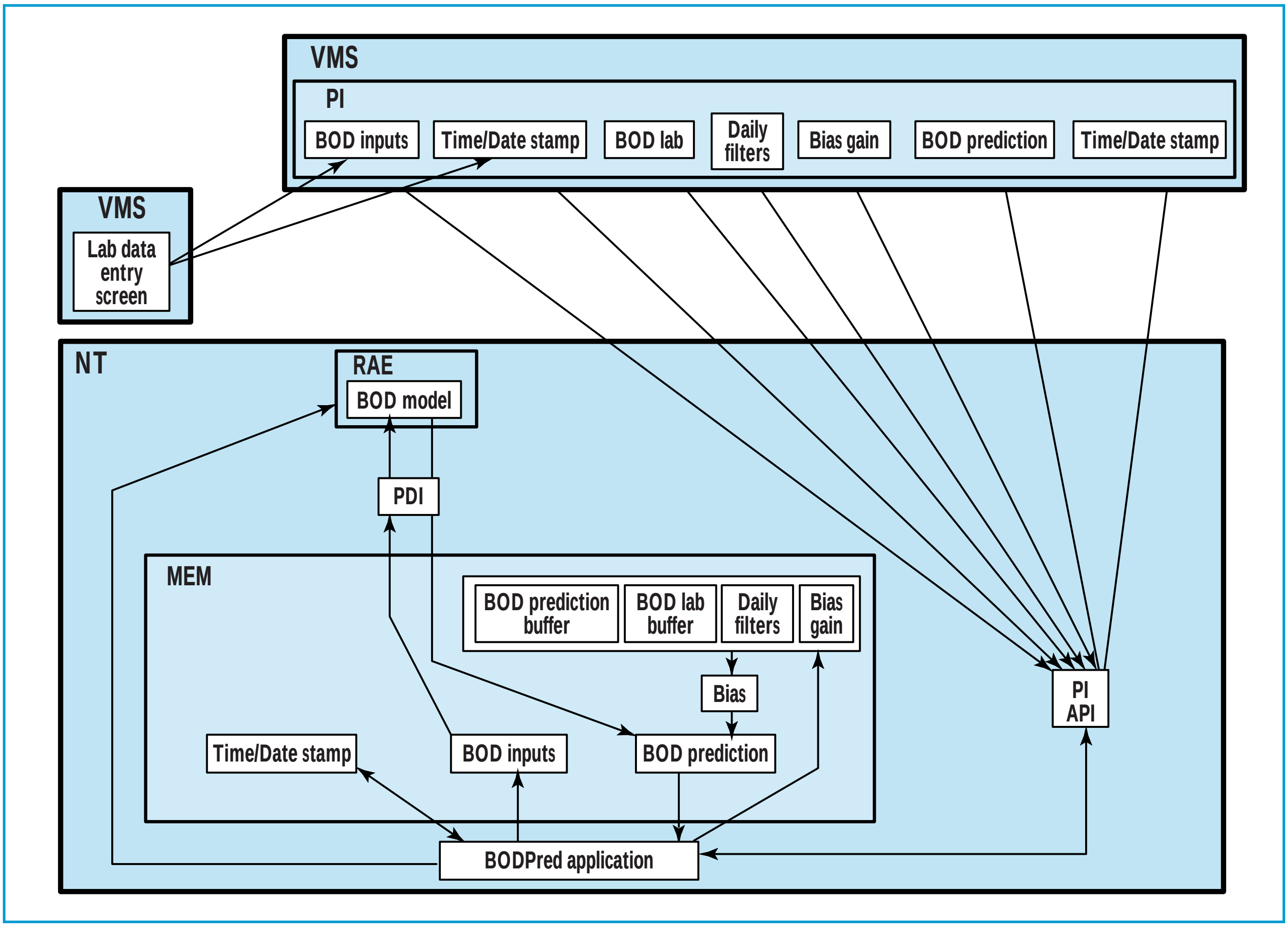
5. Predicted and measured effluent BOD during July and August 1998



6. Actual and predicted BOD between July 22 and Aug. 25, 1998 (note the bias that developed from August 15 through August 25)



7. Bias feedback algorithm with moving average



8. Flow chart of computer system and information storage for the BOD predictor

points and adding it to the new predicted BOD value. If the average error is zero, the predicted BOD value is left unchanged. However, if there is nonzero average error (i.e., there is a bias), then the predicted value is adjusted accordingly. As shown in next section, this approach is effective at removing an error if it is persistent. This method will also reduce the need to frequently retrain the model as changes occur in the plant.

The bias feedback algorithm can be implemented either in the neural network software or in the PI system itself. The algorithm runs automatically every time a new BOD measurement is entered. The bias will be multiplied by a user-specified gain, which ranges from 0 to 1. A value of 0 effectively turns off the bias so that there is no adjustment to the prediction from the model. A value of 1 completely applies the bias. Any intermediate gain value will apply a partial bias, which may be used to avoid over-responding if there is inaccuracy in any process or laboratory data.

The bias correction term can be calculated from a weighted moving average or from a first-order filter. For a first-order filter, the system would look in the PI system for the last laboratory measurement of BOD, calculate the offset to the prediction, and calculate a new bias as follows:

$$\text{New bias} = \text{Bias gain} \times [\text{Old bias} \times (1 - \text{Filter}) + (\text{Lab}_{last} - \text{Predicted}_{last}) \times \text{Filter}] \quad (1)$$

A weighted moving average bias would be a user-defined filter of the offset to the lab values in the PI system over some number of data points, as follows:

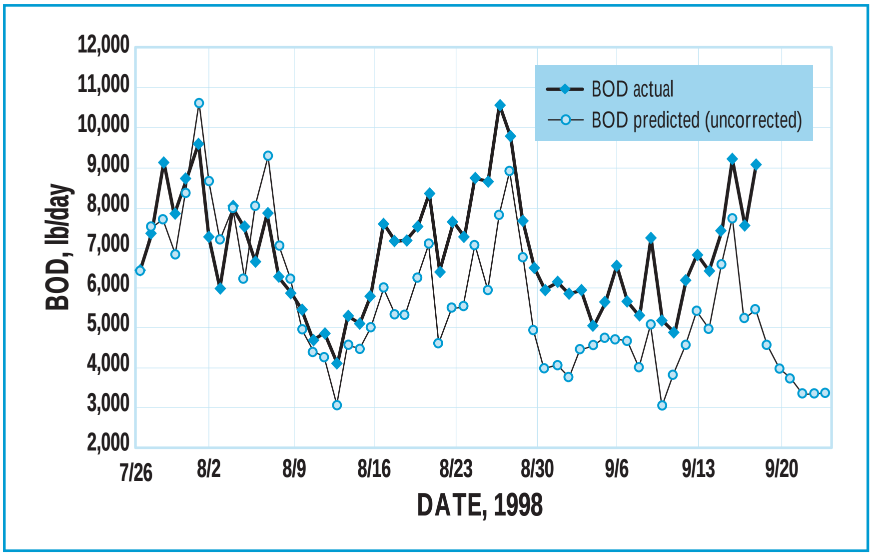
$$\text{New bias} = \text{Bias gain} \times \sum_{i=1}^{n} [(\text{Lab}_i - \text{Predicted}_i) \times \text{Filter}_i] \quad (2)$$

$$\sum_{i=1}^{n} \text{Filter}_i = 1 \quad (3)$$

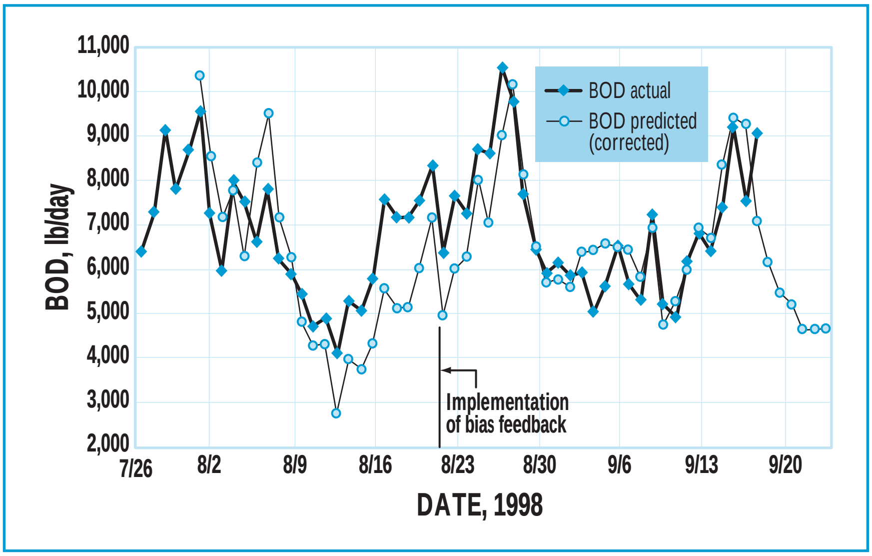
where n is the number of samples required for essentially total (99%) correction. As shown in Eqs. 2 and 3, the moving average approach allows different weights to be given to more recent data points. Therefore, the weighted moving average approach is a more flexible and robust design than a first-order filter bias. The response of biasing with the weighted moving average method following a step change and an impulse change in the error are shown in **Fig. 7.**

The first disturbance in Fig. 7 is a persistent offset of 50. The moving average effectively achieves this bias result in five sample increments. The response is replicated with a negative step. A second type of disturbance, showing an impulse error, demonstrates the response to an erroneous lab entry (outlier). The filter was designed to be relatively insensitive to outliers while achieving the desired correction after five sample increments.

The calculated bias is added to the model prediction, and the final result will be placed in the existing PI storage element for the BOD prediction, with the proper time stamp. **Figure 8** shows an illustration of the computer program, data storage, and communication system used to implement the BOD model with the bias feedback algorithm *(10)*.



9. Measured and predicted BOD for July–September 1998 (without bias feedback)



10. Measured and predicted BOD for July–September (with bias feedback) after Aug. 22, 1998

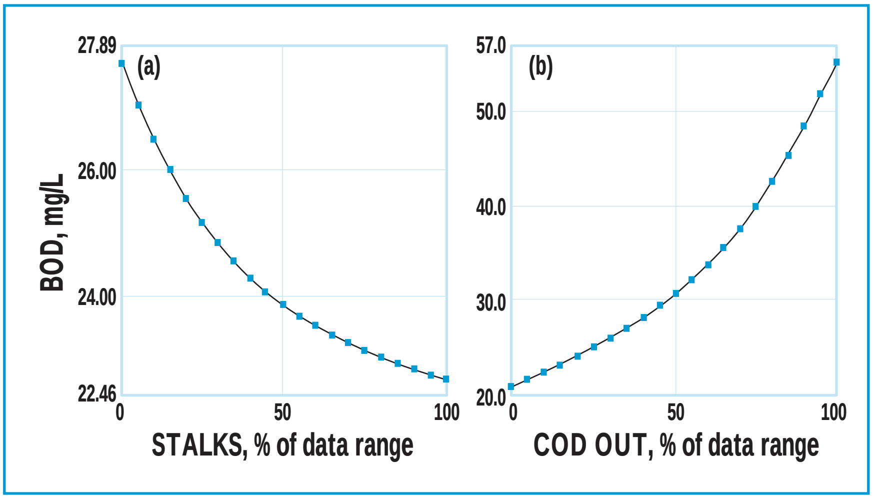
RESULTS

The results of the BOD prediction model with bias feedback algorithm are compared to the results without bias correction in **Figs. 9 and 10.** Notice that after implementation of the bias feedback algorithm on August 22, the accuracy of the BOD prediction was restored, resulting in the more accurate predictions shown in Fig. 10. The algorithm addresses short-term changes in mill operating conditions, such as changes in production schedules or equipment outages, and makes the model more robust and capable of responding to changing conditions in the mill or in the waste treatment plant.

Having a rapid feedback prior to potential high BOD excursions allows the plant operators to respond faster and to control BOD better. As shown in the right side of Figs. 9 and 10, the actual BOD measurement (thick line) provides no information on the state of the waste treatment plant until 5 days have elapsed. Operating in a safe mode, well below permitted levels, may require additional operating costs and production curtailment. Using the predicted BOD values reduces the delay to a few hours (thin line) and provides waste treatment plant and mill personnel with a way to respond faster and avoid large prolonged excursions. The delay of 12 hours for BOD predictions in this application is determined by the sampling frequency for the 11 input variables, which can be modified as appropriate. The BOD model should be retrained with recent data at least once every 6 months to adjust the basic model for changes and upgrades in the process. Retraining the model is a fairly straightforward operation that takes 1–2 hours and does not require as much data as does building the model.

FUTURE WORK

The objective of this work was to develop a method for rapidly predicting effluent biochemical oxygen demand, and this has been completed. However, the neural network



11. Relationship between effluent BOD and stalked protozoan counts (stalks) or effluent COD

model can also be used to explore the effects of input variables on BOD under intermediate conditions. Using the neural network model, the plant engineer or operator can perform setpoint changes and what-if scenarios to evaluate various approaches for improving plant operation. The model can potentially be inverted and used in high-level, closed-loop control of BOD by adding new automatic control capabilities.

After training the models, the neural network model can be used to explore the relationship between the various inputs and BOD. **Figure 11** shows the nonlinear relationship indicated between stalked protozoan counts (stalks), effluent COD, and effluent BOD. The strength of the neural network approach is that it is capable of representing the nonlinear and multivariable relationships that often exist in manufacturing operations *(11, 12)*. For example, higher stalked protozoan counts (stalks) are a good indication of lower effluent BOD; however, the relationship is less pronounced at higher values of stalks. Effluent COD has a direct correlation with effluent BOD, assuming all the other variables are held constant. Knowledge of this type of relationship can be useful in improving the operation of the waste treatment plant and, along with a rapid estimation of BOD, in improving BOD control.

CONCLUSIONS

A neural network model was developed and implemented to provide a rapid and accurate prediction of a paper mill's effluent BOD levels. The predicted BOD value is available within a few hours instead of the 5 days required for the standard BOD test, and therefore the prediction allows a more effective response to process changes or upset conditions in the waste treatment plant. The model uses eleven inputs and has an R^2 value of 0.78. Predicted BOD values are within ±10% of the actual BOD test results. The predicted BOD value is automatically updated as soon as the operator enters the 11 inputs into the process information computer. The frequency of the BOD prediction is determined by the frequency of entering the input data into the mill's process information system. A bias feedback algorithm was implemented to handle unmeasured disturbances or changes in plant operations. The model should be retrained and updated every 6 months.

The biochemical oxygen demand prediction model has helped one integrated pulp and paper mill improve its environmental performance while reducing production curtailments during critical periods. Implementation of the neural network model resulted in a cost avoidance approaching US$ 1 million during 1998. Production personnel are reporting the predicted BOD values at daily production meetings and using them in guiding overall strategies for plant and mill operation. This approach to rapid BOD predictions can help the paper industry improve operating efficiency and environmental performance. TJ

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LITERATURE CITED

1. Eaton, A. D., Clesceri, L. S., and Greenberg, A. E., *Standard Methods,* 19th edn., American Public Health Association, American Water Works Association, Water Environment Federation, Washington, 1995, pp. 5-3 to 5-12.
2. Smith, M., *Neural Networks for Statistical Modeling,* Van Nostrand Reinhold, New York, 1993, pp. 97–115.
3. Zornetzer, S. F., *An Introduction to Neural and Electronic Networks,* Academic Press, San Diego, 1994, p. 32.
4. Brookman, S. K. E., *Water Res.* 31: 372(1997).
5. Reynolds, D. M. and Ahmad, S. R., *Water Res.* 31: 2021(1997).
6. Riedel, K., *Frontiers in Biosensorics II* 81: 99(1997).
7. Anon., *Process Insights Users Guide,* ver. 4.1, Pavilion Technologies, Austin, TX, 1997.
8. Wang H., Wang, A. P., and Duncan, S., "Advanced process control in paper and board making," Pira technology series, Pira, Leatherhead, U.K., 1997, pp.113–147.
9. Anon., *Insights '98 Pavilion Users' Group Conference Proceedings,* Pavilion Technologies, Austin, TX, 1998.
10. Glowka, R., Pavilion Technologies, Austin, TX, personal communication.
11. Leslie Grady, C. P., Jr. and Lim, H. C., *Biochemical Wastewater Treatment: Theory and Applications,* Marcel Dekker, New York, 1980, pp. 55–59.
12. Gray, N. F., *Activated Sludge Theory and Practice,* Oxford University Press, Oxford, U.K., 1990, pp. 27–33.