A model-based approach to predicting BOD_5 in settled sewage

D.A. Brydon and D.A. Frodsham
Wastewater Services, North West Water Ltd, Warrington, WA5 3LP, UK

Abstract Rapid, accurate and reliable measurements of BOD are a very desirable basis for monitoring and controlling wastewater treatment works. Unfortunately, however, producing satisfactory measurements using hardware instrumentation has proved difficult. This paper addresses the issue of BOD estimation using a model-based approach. Two models are developed from historical data using neural network methods. The first model estimates the five-day BOD of the settled sewage using flow, solids, chloride and ammonia data and produces accurate predictions. The second model uses only flow and solids data as inputs yet still produces acceptable (although less accurate) predictions. It was concluded from this that satisfactory estimates of five day BOD can be produced using information that is relatively common to most works. The models are straightforward to apply on-line and offer a method of estimating five day BOD in real-time that is likely to be cheaper, more reliable and easier to maintain than hardware instrumentation.
Keywords BOD; model; neural network

Introduction

The proposals published by the British Royal Commission on Sewage Disposal indicate that biochemical oxygen demand (BOD) has been used as a measure of the organic content of wastewater for over 100 years (Bailey and Ollis, 1984). Despite this long history of widespread use there are, however, limitations associated with the determination of BOD. Metcalf and Eddy (1991) note five restrictions and state that the most notable is the time required to generate an estimate of BOD. This can be sub-divided into two aspects: firstly, although BOD_5 is a commonly used variant of BOD, the five day period may not correspond to the amount of time required to consume all of the soluble organic material (Metcalf and Eddy, 1991). Secondly, a measure of the organic content of wastewater is a desirable basis for controlling treatment works if the operating conditions are to be manipulated to enable the plant to cope with varying loads. This is only possible if accurate estimates of BOD are available much more frequently than at five day intervals. Unfortunately, laboratory BOD analyses that take five days to complete are not a suitable foundation on which to base a control scheme due to the lag between collection of the sample and the measurement of BOD becoming available. For example, a feedback control scheme based on five day BOD will only be able to react to the wastewater quality five days earlier and will not be able to compensate for disturbances that have occurred in the intervening period.

The work presented in this paper describes a model-based approach to providing rapid and accurate estimates of BOD_5. The overall aim of the work was to develop a model that is suitable for on-line use, hence the model clearly must be based on wastewater quality variables that are also straightforward to measure on-line. Literature concerning hardware for measuring BOD on-line is also discussed. A case study is presented based on a wastewater treatment works (WwTW) where the organic loading of the primary effluent will have an impact on the operation of a new biological secondary treatment stage. Consequently, the objective of the work was to produce an accurate model describing the BOD_5 trends of the primary effluent. The operating strategy proposed during design is based solely upon the flow entering secondary treatment and this may need to be modified to cope with

Water Science and Technology **Vol 44 No 2–3 pp 9–15** © IWA Publishing 2001

situations of low flow but high organic load. Consequently it is desirable to have readily available estimates of the organic content of the primary effluent.

Relevant literature

Hardware instrumentation is available for the measurement of BOD over short-periods of time. Spanjers and Klapwijk (1990) and Kalte (1999) all discuss such hardware although, while reporting relatively smooth operation and satisfactory accuracy, fail to provide a detailed discussion of potential limitations to this type of instrument. Furthermore, these instruments tend to indicate the short-term BOD (e.g. 3 minutes in the case of Kalte, 1999) whereas five-day BOD is the more usual measure.

The modelling methods described here have been used widely in industries such as chemical, petrochemical and pharmaceutical production. The majority of published work uses empirical modelling techniques such as regression, time-series and neural networks. For example, Willis *et al*. (1992) used a neural network model to predict the quality of biomass in a fermentation process at a rate that was much faster than that at which laboratory measurements were available. Mitchell *et al*. (1995) used a similar approach to develop a model that could predict the quality of a product from a lubrication plant, again leading to estimates that were available much more frequently than from the laboratory. These techniques are often incorporated into control schemes so that the more frequent estimates can be used as a basis for on-line process control. The chemical and process engineering industries in particular have a long history of model-based process control. For example, Bhat and McAvoy (1989) and Psichogios and Ungar (1991) both describe neural network-based schemes for the control of a reactor system while Baratti *et al*. (1995) present an approach based on mechanistic modelling to estimating, in real-time, the compositions of the products from a distillation column. Turner *et al*. (1996) also consider model-based control of a distillation column and report significant potential savings in operating cost due to the improved control resulting from the scheme.

Although the chemical industry has made a substantial contribution to the more widespread use of model-based techniques, a number of significant water and wastewater applications have also been reported, particularly for activated sludge plants (Zhao *et al*., 1994, Zhao and Kummel, 1995, Lukasse *et al*., 1998 and Yu *et al*., 1998). Model-based approaches to predicting BOD and other wastewater quality parameters are discussed by Ellis *et al*. (1990) and Hiraoka *et al*. (1990). More recently Kolisch *et al*. (1998) have described an on-line model-based system for optimisation of a wastewater works while Hajda *et al*. (1998) present a model-based real-time control scheme for a sewer collection system.

The following sections describe the development of an empirical model, based in particular on the neural network approach presented by Willis *et al*. (1991), of the BOD_5 trends in the primary effluent at this WwTW. The case study is described in the next section and subsequent sections discuss the analysis of the available data and the development of the model.

Case study

At the time of writing (October, 1999), the WwTW consisted of primary treatment only and was being extended to include secondary treatment in the form of 20 biological aerated flooded filter (BAFF) cells. This works has a large urban catchment with a significant industrial effluent contribution and, under the proposed operating regime for the extended works, the number of BAFF cells in operation at a given time will depend upon the flow to the works. Although this scheme will maintain a minimum hydraulic loading rate through each BAFF cell it is possible that for a given range of flow the organic load entering the plant may exceed the allowable maximum.

The current control system selects the number of cells in service at a given time to be that giving a desired hydraulic loading rate. A rise in flow causes more cells to be brought on-line and when flow falls cells are taken out of service. The design of the WwTW is based on an average number of cells being required over the day. Hence, at periods of high flow there may be many cells in operation while during low flow conditions fewer may be required. It is quite possible, however, that the number of cells selected on the basis of flow is not sufficient to cope with the actual organic loading. For example, a high organic loading may coincide with a period of low flow. At present, all the BAFF cells will be brought on-line if a high organic loading is suspected. This does not, however, guarantee that the minimum hydraulic loading rate will be achieved and may lead to settling of the media within the BAFF cells thus leading to failure of the system and exceedance of the consent for the works.

Hardware instrumentation for measuring the BOD in the BAFF influent has been evaluated at this WwTW with unsatisfactory results. Consequently model-based methods of inferring the BOD of the BAFF influent were investigated with the objective of developing a model that could be incorporated in a system capable of overriding the flow control should the primary effluent contain a high organic load. Clearly, the evaluation of model-based approaches to this problem requires that sufficient process data are available – an issue that is discussed in the following section.

Available data

A set of primary effluent data was collected covering the period from the January 1992 to February 1999. This data set consisted of measurements of suspended solids, flow, ammonia, chloride, BOD and COD. The interval at which each variable was sampled, however, was not consistent. Moreover several gaps were deemed too large to be approximated by interpolation and this precluded the use of one particular empirical modelling procedure. Dynamic empirical models use a time-series of past data to predict current and future trends. This type of model relies on the input data being part of a time-series comprising measurements sampled at a consistent frequency. Consequently gaps in the time-series can hinder the development of a dynamic empirical model if the missing values cannot be interpolated or otherwise approximated. Given that this was the case with the data used here a static model was deemed more appropriate. Static models use current information to generate estimates of current trends and can be an elegantly straightforward approach to generating real-time estimates of variables that are typically difficult to measure on-line (Willis *et al*., 1992).

Outliers in the data were identified and removed while for each variable in the data set the range was determined and a histogram analysis was performed. The maxima and minima of the data indicate the upper and lower limits of the operating range of the model while the histogram analysis reveals the distribution of the data between these extrema. It is important to bear in mind that, while models of this type should not be used outside the range of the data used for development, it is equally unwise to use a model in areas between the upper and lower limits where data are sparse (Doherty *et al*., 1997). A percentile analysis was also carried out to enable the peak values of the model to be compared with those of the measured data. This analysis was also used to partition the data into development and test sets. The former is used to calculate the coefficients of the model while the latter is used to evaluate the model on a completely fresh set of data. To ensure that this fresh data set covers the full operating range of the process it was constructed by selecting 25 samples from each quartile of the full data set.

Model development and testing

Empirical models make use of the process information that features implicitly in measured data and are generally not based explicitly on the fundamental chemical, physical and biological theory that describe the system being modelled. Neural networks are one such empirical approach and although these techniques have suffered from a mixed reputation in the past, the last decade has seen a growing acceptance of them as a valuable process engineering tool. The theory of neural networks is well documented and will not be re-produced here; Willis *et al*. (1991) and Turner *et al*. (1996) provide concise introductions to the theory and its role in process modelling. The models described in this work were developed using MATLAB software and the "train-and-test" technique. Developing a neural network is an iterative process and, if the model is not tested at regular intervals, it can "overfit" the data. Overfitting occurs when a model matches one set of data so closely it is unable to generalise to other data sets. One straightforward method of avoiding this is to test the model at the end of each iteration using a different set of data and halt model development when the ability of the model to estimate the second set of measurements degrades. This procedure was followed in this work using the development and test data sets.

The data set was used to derive two models. The first model used the settled sewage flow, suspended solids, ammonia and chloride measurements as inputs to estimate the settled sewage BOD_5 (this model is referred to as Model 1). Only the settled sewage flow and suspended solids were used as inputs to the second model (referred to as Model 2). Thus, the data set used to develop the first model consisted of 903 samples of the model inputs and settled sewage BOD_5 and 100 samples for testing. For the second model, the data set consisted of 1572 samples of the model inputs and settled sewage BOD and 100 samples of test data. While the ideal situation would be to supply as much on-line information as possible to the model this may not be realistic. Hence, the two models have been developed to determine if acceptable estimates can be produced from a limited amount of relatively inexpensive and readily available information (i.e. flow and solids) or whether other, more costly, instrumentation is necessary. Note also that for each set of input data the models are estimating the corresponding five day BOD. If used on-line then each model would give an instantaneous estimate of the five day BOD that could be expected if standard laboratory tests were performed.

Each model input was scaled to lie in the range 0 to 1 to reduce the effects of widely differing magnitudes of input data that could lead to a biased model. The model output was scaled in an identical fashion. This scaled model data set was then used to develop a neural network model of the BOD_5 entering the secondary treatment stage at the WwTW.

For clarity, the comparisons of the measured and modelled trends are presented on two separate plots. Furthermore only the last 500 samples are shown so as to avoid congested figures. This portion of data provides a clear illustration of the ability of the models to estimate peak values of BOD_5. Figures 1 and 2 compare the actual settled sewage BOD_5 trend with those estimated by the two models. Both models produce accurate estimates of the BOD trend in the development data set over the range 30 to 221 mg/l. Model 1, however, estimates the peaks and troughs of the trend more accurately than Model 2. This was anticipated since the additional data available to Model 1 provides more information relevant to the extreme values of BOD. The accuracy of the model estimates was quantified using the average absolute error, E_{abs}, which is defined as follows:

$$E_{abs} = \frac{1}{n}\sum_{i=1}^{i=n} abs\left(y_i - \hat{y}_i\right)$$

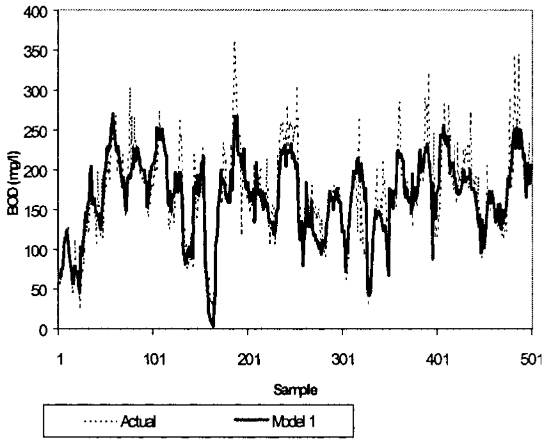

Figure 1 Estimates from Model 1

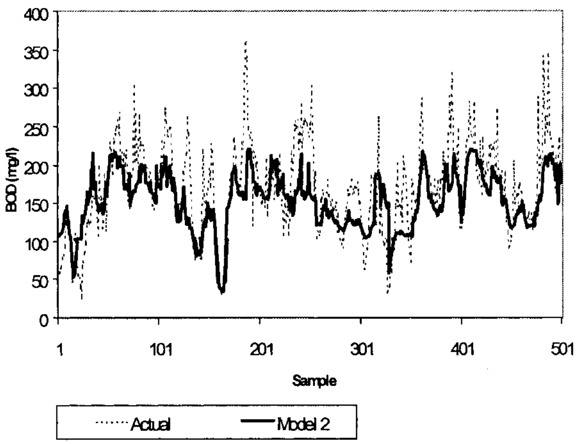

Figure 2 Estimates from Model 2

where: n = the number of samples of settled sewage BOD_5 data to be modelled; y_i = the i^{th} sample of settled sewage BOD_5 data; $\hat{y}_i$ = the model estimate of the i^{th} sample of settled sewage BOD_5 data. The error measures for both models, and the respective 95% confidence limits, are shown in Table 1.

Discussion

The models presented in the preceding section reveal that accurate estimates of the settled sewage BOD_5 trend at the WwTW can be generated using the available process data. In particular, the model based solely on flow and suspended solids demonstrates that satisfactory estimates can be produced using information that is commonly recorded at most WwTW. This is significant if on-line modelling is to be considered since this work indicates that good predictions of organic load can be made in real-time if on-line flow and suspended solids data are available. Although there is clearly the issue of fouling to consider when using suspended solids (or even turbidity) instruments in wastewater environments, the cost of installing the on-line monitors needed for a model of this type are likely to compare

Table 1 Average absolute errors for the models

	Model 1	Model 2
Average absolute error	23 ± 1.40 mg/l	39 ± 1.54 mg/l

favourably with those for dedicated BOD measuring hardware. In addition, the model is straightforward to update when new data become available and is likely to require less recalibration than a hardware instrument. Furthermore, the models presented here both give an instantaneous estimate of the five-day BOD whereas hardware instruments typically produce estimates of "short-term" BOD. Given that the five-day BOD is the most commonly applied and understood measure and is used for setting regulatory consents, the model-based approach offers real-time tracking of BOD_5.

One limitation of using only flow and suspended solids, however, is the inability of the model to fit the larger peaks of the BOD_5 trend. Previous experience with this type of model demonstrates that, subsequent to development, they are generally unable to produce predictions that exceed the largest value predicted during model development (i.e. the upper prediction limit). In this particular case the highest BOD_5 predicted by model 2 was 221 mg/l. It is anticipated that if, in future on-line applications, this model is presented with flow and solids measurements that indicate a BOD_5 above this value then the model outputs will "saturate" at this upper prediction limit. Thus, while the model is limited in that it has an upper limit beyond which it cannot predict, the fact that the predictions "saturate" would at least provide an indication of the BOD_5 level. Neither model exhibits an appreciable saturation effect at lower BOD_5 values.

As noted in the literature survey, models of this type have a sound track-record when applied in on-line situations. Given that many wastewater (and water) sites have SCADA capability, and also noting that many systems can communicate with spreadsheet software, this type of model-based approach offers a promisingly inexpensive approach to real-time measurement of variables that have typically proved difficult to measure reliably using hardware. In this particular case the cost of development was relatively low since the data used to construct the model were already available (i.e. as an historical data set). Moreover, since the model does not depend on a time-series of input data it is insensitive to the sampling frequency of the available measurements. This suggests that any data collection exercises that may need to be carried out to acquire the data to build a model do not necessarily have to fit to a rigid sampling regime. This extra flexibility can also be used to reduce the costs of data collection.

Conclusions

This work has demonstrated that the BOD_5 trends in the settled sewage at the WwTW could be predicted with acceptable accuracy using only inlet flow and suspended solids as model inputs. This approach is relatively straightforward to implement on-line, should such facilities be available, and could offer real-time predictions of five-day BOD whereas hardware instruments typically measure short-term BOD. It was concluded that this is a significant feature of this approach since BOD_5 is the more commonly used and readily understood measure. Given that the modelling approach adopted here is insensitive to the sampling frequency of the data it was also concluded that the use of historical data to develop such a model can reduce the need for (and hence cost of) data collection exercises. Finally, past work in other areas has indicated that this type of model-based approach has the potential to be used in estimating a range of variables that are typically troublesome to measure using hardware. This suggests that such models can be a relatively cost-effective method of measuring or inferring key (but difficult to measure) variables.

References

Baratti, R., Bertucco, A., Da Rold, A. and Morbidelli, M. (1995). Development of a Composition Estimator for Binary Distillation Columns. Application to a Pilot Plant, *Chem. Eng. Sci.*, **50**(10), 1541–1550.

Bhat, N. and McAvoy, T.J. (1989). Use of Neural Nets for Dynamic Modelling and Control of Chemical

Process Systems, *Proceedings of the American Control Conference*, 1342–1347.
Bailey, J.E. and Ollis, D.F. (1984). *Biochemical Engineering Fundamentals*, 2nd Ed., Singapore, McGraw-Hill Inc.
Doherty, S.K., Gomm, J.B. and Williams, D. (1997). Experiment Design Considerations for Non-linear System Identification Using Neural Networks, *Computers chem. Engng*, **21**(3), 327–346.
Ellis, G.W., Ge, X. and Grasso, D. (1990). Time series analysis of wastewater quality, *Instrumentation, Control and Automation of Water and Wastewater Treatment and Transport Systems (Adv. Wat. Pollut. Control no 10)* ed. R. Briggs, London, IAWPRC-Pergamon, pp441–447.
Hajda, P., Novotny, V., Feng, X. and Yang, R. (1998). Simple feedback logic, genetic algorithms and artificial neural networks for real-time control of a collection system, *Wat. Sci. Tech.* **38**(3) 187–195.
Hiraoka, M., Tsumura, K., Fujita, I. and Kanaya, T. (1990). System Identification and Control of Activated Sludge Process by use of Autoregressive Model, *Instrumentation, Control and Automation of Water and Wastewater Treatment and Transport Systems (Adv. Wat. Pollut. Control no 10)* ed. R. Briggs, London, IAWPRC-Pergamon, pp121–128.
Kalte, P. (1999). The Continuous Measurement of Short-Time BOD, *Instrumentation, Control and Automation of Water and Wastewater Treatment and Transport Systems (Adv. Wat. Pollut. Control no 10)* ed. R. Briggs, London, IAWPRC-Pergamon, pp59–65.
Kolisch, G. and Londong, J. (1998). An on-line simulation to support the operation of municipal sewage plants, *Wat. Sci. Tech.* **38**(3) 71–78.
Lukasse, L.J.S, Keesman, K.J., Klapwijk, A. and Van Straten, G. (1998). Optimal control of N-removal in ASPs, *Wat. Sci. Tech.* **38**(3) 255–262.
Metcalf and Eddy Inc. (1991). *Wastewater Engineering: Treatment, disposal and reuse*, 3rd edition, McGraw-Hill Inc.
Mitchell, A., Willis, M.J., Tham, M.T., Johnson, N. and Bitar, S.S. (1995). Data analysis and inferential estimation applied to a lubricant production plant, *Proc. Amer. Cont. Conf.*
Psichogios, D.C. and Ungar, L.H. (1991). Direct and Indirect Model Based Control Using Artificial Neural Networks, *Ind. Eng. Chem. Res*., **30**, 2564–2573.
Spanjers, H. and Klapwijk, A. (1990). On-line meter for respiration rate and short-term biochemical oxygen demand in the control of the activated sludge process, *Instrumentation, Control and Automation of Water and Wastewater Treatment and Transport Systems (Adv. Wat. Pollut. Control no 10)* ed. R. Briggs, London, IAWPRC-Pergamon, pp67–77.
Turner, P., Montague, G.A. and Morris, J. (1996). Nonlinear and direction dependent dynamic process modelling using neural networks, *IEE Proc.-Control Theory Appl.*, **143**(1), 44–48.
Willis, M.J., Montague, G.A., Di Massimo, C., Tham, M.T. and Morris, A.J. (1991). Artificial Neural Networks in Process Engineering, *IEE Proc. Pt. D.*, **138**(3), 256–266.
Willis, M.J., Montague, G.A., Di Massimo, C., Tham, M.T. and Morris, A.J. (1992). Artificial Neural Networks in Process Estimation and Control, *Automatica*, **28**(6), 1181–1187.
Yu, R.-F., Liaw, S.-L., Chang, C.-N. and Cheng, W.Y. (1998). Applying real-time control to enhance the performance of nitrogen removal in continuous flow SBR systems, *Wat. Sci. Tech.* **38**(3) 271–280.
Zhao, H., Isaacs, S.H., Soeberg, H. and Kummel, M. (1994). Nonlinear optimal control of an alternating activated sludge process in a pilot plant, *J. Proc. Cont*., **4**(1), 33–43.
Zhao, H. and Kummel, M. (1995). State and parameter estimation for phosphorus removal in alternating activated sludge process, *J. Proc. Cont*., **5**(5), 341–351.