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Investigation of a MBR membrane fouling model based on time series analysis system identification methods

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ABSTRACT

Flux stepping tests were carried out on a novel sidestream MBR pilot plant treating industrial wastewater, and a membrane filtration unit treating tertiary quality municipal effluent. This included offline tests measuring mixed liquor concentrations, as well as soluble microbial product (SMP) levels in the sludge water which is the main irreversible foulant on the membrane [1]. A basic phenomenological dead-end filtration model that includes the three main fouling mechanisms mentioned in Hermia (i.e., cake build-up, complete pore blocking, and pore constriction) and that was based on a constant TMP operation was extensively modified [2,3]. Modifications and add-ons to this basic model included: alteration so that it could be used for varying flux and varying TMP operations; inclusion of a backwash mode; it described pore constriction (i.e., irreversible fouling) in relation to the concentration of SMP in the liquor; and, it could be used in a crossflow scenario by the addition of scouring terms in the model formulation. Using data collected from both the pilot plant and the filtration unit, this modified deterministic model was calibrated and validated in Matlab©. In order to see whether a simpler model could be formulated for advanced control purposes that was based wholly upon measured historical data sets for both the pilot plant and the filtration unit, a further conceptual model was developed based on system identification procedures and input-output times series analysis methods [4]. This model form utilised an autoregressive subspace state-space formulation. Again using the same data collected from both the pilot plant and the filtration unit, this alternative model was calibrated and validated in Matlab©. A very good correlation was shown between the measured and the expected flux decline/recovery for the phenomenological model, although a complex genetic algorithm procedure was needed for parameter estimation. The subspace model was almost as accurate as the phenomenological model even though it only used a single shot fast algorithm for parameter estimation. Further and longer historical data sets are needed to ascertain whether this second simpler modelling approach can be improved upon.

Keywords: Wastewater; MBR; Membrane; Fouling; SMP; Modelling; System identification; Time series

1. Introduction

The focus of this research was to create practical membrane bioreactor (MBR) computer models that can then be applied to MBR plant design, control and optimisation. It was intended that the outputs of this research would lead to both the improvement of existing models and the creation of new, innovative models. The eventual application of both model types would be to optimise a real treatment plant and thereby eventually develop a long term energy saving control strategy. Consequently this research work uses phenomenological models based on both traditional MBR filtration and biochemical processes to measure the effectiveness of alternative time series input-output models based upon system identification methods. Both model types are calibrated and validated using the same plant layouts and data sets derived for this purpose.

1.1. Problems with using phenomenological membrane fouling models for design, operation and control of MBR plant

For a MBR system treating wastewater, capturing membrane fouling phenomena in the form of mathematical models has been a task of many different research teams around the globe for the past decade. Most researchers model the membrane fouling process using a phenomenological mechanistic approach that obeys the basic laws of physics and can be deduced from first principles and scientific theories. Although this is the traditional approach taken when modelling MBR systems, it does suffer from the following disadvantages:

- As membrane fouling is in reality a very complex and very little understood process at this moment in time, it is difficult to make a generalised mechanistic fouling model that can adequately address all issues and specific nuances involved.
- Fouling models of this type need to be made bespoke for each individual filtration system on a case-by-case basis. This is especially true for the hydrodynamics of the process (e.g., type of sparging system or membrane scour system in use), and the membrane operational regime (e.g., submerged or sidestream or vertical air-lift).
- The models are often highly dimensional and contain numerous parameters that need determination by specific plant data, specific process operation (i.e., flux stepping trials) and extended specialist laboratory experiments (e.g., specific cake resistance tests). Thus they can be over-parameterised with too many degrees of freedom.
- Parameter estimation and optimisation can prove to be a convoluted and complex procedure requiring expert knowledge and experience.
- For many applications insufficient data is available to allow a full model calibration and validation, and thus the verified model is not omnipotent for every situation.
- The general application of such complex models, which in themselves require considerable calibration experience to give sufficient predictive accuracy, means their take up for process control and the development of future operational strategies will always prove limited [5].

In order to overcome the inherent deficiencies in the traditional approach, a growing group researchers are utilising non-traditional modelling approaches to describe the membrane filtration and fouling process for a MBR.

1.2. Input-output (IO) models as a possible alternative – time series system identification methods

In an ideal world, a quick and easy approach to wastewater treatment modelling is required that can be easily applied to a real life situation. This would ideally be coupled with very simple calibration procedures so that any model can be constantly "retrained" on newer plant data sets as and when they become available. Since this "retraining" would prove straight forward, it could be performed as many times as necessary. To make this proposed new approach easy to apply, it should not require an intimate knowledge of the exact processes occurring in the MBR, so it could be applied by any non-specialist who was new to wastewater treatment modelling [6].

Very few alternative approaches have been used to date when compared to the traditional mechanistic models developed for wastewater treatment plant [7]. This is mainly because wastewater treatment modellers and users come from an engineering background and therefore are unlikely to have an intimate knowledge of non-traditional approaches used in other disciplines such as the economics field. The bulk of alternative approaches used in wastewater treatment modelling have centred around either multivariate statistical methods or on an artificial intelligence systems where expert knowledge of the process is quantified and the developed system is then "trained" to provide accurate prediction. Of these expert knowledge systems, the most commonly investigated are the artificial neural network (ANN) methods and fuzzy neural networks (FNN) [8].

A lesser known approach is time series modelling using autoregressive models. It is more commonly used in econometric system forecasting for international financial markets [4]. It has only been used in a limited manner for wastewater treatment modelling, and even then, only for the simple modelling of effluent leaving a plant [9]. It has been hypothesized under this study that a formulation based on simplified input-output (IO) times series models, should be developed as an alternate, simpler and faster way of calibrating and verifying MBR wastewater treatment models. This would mean that the exact nature of the biology in the bioreactor and its effects on the membrane fouling process need not be fully understood, as the time series models would be based solely on historical IO data sets that would be used to predict future plant output. This procedure if it proves effective is largely linearised around an operating point or range so that any solutions are easily obtained. It would then be very useful for plant control and operation, and be much quicker to develop than a phenomenological model since an intimate knowledge of the physics and chemistry behind the process is not required. Additionally, complex theory and mathematics to describe this theory would not be needed thus again saving time in model development [6].

1.2.1. "Model conceptualisation procedure" required to embed the IO model in reality

Under this study two different model types, namely a phenomenological model structure and a IO times series model structure, were tested to ascertain which gave best results. The main research questions posed were:

i) How easy is it in practice to calibrate and validate a relatively simple phenomenological membrane fouling model for a real life MBR plant which is still rich enough in complexity to express the major membrane fouling mechanisms involved?
ii) Is a system identification procedure using time series analysis a simpler, quicker modelling approach to use to determine membrane fouling within a real life MBR plant? Can an IO model give the same degree of accuracy as a phenomenological model? Is it as useful? Is it as robust?

An IO models based on standard mathematical formulations such as ordinary differential equations or difference equations of various orders can be used as a quick method for model prediction as no prior process knowledge is required for model calibration and validation [4]. The procedure automatically selects the best order model based on the number of lags in output data that give the optimal prediction. Little skill is needed by the simulator to obtain best fit, and a significant amount of time is saved when compared to the complex needs of verifying a typical mechanistic model. Additionally, many of the complex tests, both laboratory based and in-situ, that are required to valid numerous model parameters are not required, or the need to carry out extensive literature reviews of parameter values used by previous reputable researchers.

However, it is recommended if these model types are used as real practical alternatives to phenomenological approaches, extreme care should be taken in selecting appropriate variables when forming the IO model structure. This is where a "model conceptualisation procedure" developed by prior researchers will prove invaluable as it underpins the basic knowledge needed by a lay person when developing models of this type [6]. This procedure means that various IO structures have already been developed and tested based on biochemical and hydrodynamic process knowledge, and the user only has to implement them. Fig. 1 describes part of such a MBR "model conceptualisation procedure" developed under this study [6].

An IO model structure seems appropriate to be used both for flux stepping data sets as well as long term standard filtration data sets. Additionally, an input-output model structure can be used irrespective of the membrane configuration or operational regime i.e., constant flux/varying trans-membrane pressure (TMP) or constant TMP/varying flux; sidestream crossflow or submerged systems.

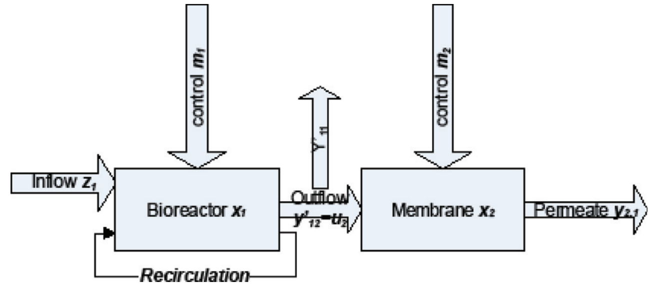

Fig. 1. Part of a "model conceptualisation procedure" used to develop rational relationships between IO variables for an approximate decomposed MBR model (Source: Paul 2010).

2. Description of models utilised

A comprehensive phenomenological membrane fouling model was developed from a basic version initially produced by Duclos-Orsello in 2006 [2]. Once calibrated and validated, this modified model was then tested on data sets taken from real life plant. Using these same data sets, several linear IO fouling models based on a specialised "model conceptualisation procedure" were tested as alternative model structures.

2.1. Phenomenological model used - Duclos-Orsello (2006)

Several classical fouling studies use a three mechanism model for the biofouling process: a) pore constriction; b) pore blockage; and, c) cake filtration [3], [10]. These mechanisms can be directly related to the main bio-fouling processes observed in a MBR system. The Duclos-Orsello (2006) model was chosen under this study as it contains all three main fouling mechanisms, and is sophisticated enough with sufficient degrees of freedom whilst still being relatively simple in structure with a limited number of model parameters requiring calibration [2]. In a bid to make this model more practical and usable for a typical MBR plant situation, the generalised Duclos-Orsello (2006) approach was extensively modified under this study [11].

2.1.1. Extensions to Duclos-Orsello (2006) model

Further re-modifications and add-ons to this model include [6]:

- It can now describe pore constriction (i.e., irreversible fouling) in relation to the concentration of SMP in the liquor which is the main culprit deemed to instigate membrane fouling.

- It can be used in either a sidestream crossflow or a submerged scenario by the addition of membrane scouring terms in the model formulation.
- It has been further altered so that it can be used for constant flux and varying TMP operation.
- A backwash mode with clean membrane area reset now forms part of the model.

2.1.2. Total flow through membrane for constant TMP/varying flux operation

A summary of the re-modified equations with additional terms is provided as follows:

$$Q_{total} = Q_u + Q_b \tag{1}$$

where unblocked flow, Q_u is:

$$Q_u = J_u A_u \tag{2}$$

with $\frac{dA_u}{dt} = -\alpha Q_u C_b = -\alpha J_u A_u C_b$ and

$$\frac{dJ_u}{dt} = \frac{-2\beta Q_0 S_{smp}}{\sqrt{J_0}} (J_u)^{\frac{3}{2}}$$

where blocked flow, Q_b is:

$$Q_b = \frac{TMP}{\mu\left(R_{inb} + R_p\right)} A_b \tag{3}$$

with $\frac{dA_b}{dt} = -\frac{dA_u}{dt} = \alpha J_u A_u C_b - k_b(A_{0(bw)} - A_u)$ and $\frac{dR_{inb}}{dt} = \beta Q_0 C_b \sqrt{R_m}\sqrt{R_{inb}}$ and $\frac{dR_p}{dt} = f' R' J_b C_b - k_p R_p$

2.1.3. Total flow through membrane for constant flux/varying TMP operation

Eq. (3) for the blocked flow, Q_b, is reformulated as follows:

$$\mu \cdot \frac{dTMP}{dt} = J_b\left(\frac{dR_{inb}}{dt} - \frac{dR_p}{dt}\right) + (R_{inb} + R_p)\frac{dJ_b}{dt} \tag{4}$$

2.1.4. Backwashing

Since both the pilot MBR plant and the membrane filtration unit are backwashable, this needs some representation in the model. This backwash effect is simply included by resetting of cake resistance and blocked membrane area by a specifiable amount after the backwash step has been completed. This reset can be altered to cater for full cake and membrane area recovery or only partial recovery. For simplicity's sake, it is assumed that changing between normal operation and the backwash mode occurs instantaneously.

2.2. IO models used – autoregressive model structures

System identification is an iterative process in which models with different structures are identified from data, and the individual model performance compared. The normal start point is by estimating the parameters of very simple model structures. If the performance still proves poor, then the model structure is gradually increased in complexity. Ultimately the simplest of all model structures tested is eventually selected that best describes the dynamics of the system under scrutiny. In this iterative process, which can be automated, the system identification procedure commences by initially using linear continuous IO polynomial model structures, such as autoregressive exogenous (ARX) and autoregressive exogenous moving average (ARMAX) ones. Later on linear continuous IO state-space model structures are also tested using the supplied times series data [4]. The best fit structure is then chosen as the optimal model formulation.

Incidentally the ARX model is the simplest one of a group of linear prediction formulas based upon a general linear case. This model type attempts to predict an output $y[n]$ of a system based on the previous outputs ($y[n-1]$, $y[n-2]$...) and inputs ($x[n]$, $x[n-1]$, $x[n-2]$...). Deriving the linear prediction model for the estimated output, $y_e[n]$, involves determining the coefficients a_1, a_2, .. and b_0, b_1, b_2, ... in Eq. (5).

$$\begin{aligned} y_e[n] = {} & a_1 y[n-1] + a_2 y[n-2] \ldots \\ & + b_0 x[n] + b_1 x[n-1] + b_2 x[n-2] + \ldots \end{aligned} \tag{5}$$

An ARX model formulation is simple and has good noise-to-signal ratios, while the ARMAX is designed when the dominate disturbances enter via the input states which is the case for wastewater treatment plant. The state-space models are first order versions of the autoregressive form that utilise intermediate state vectors in the calculation procedure. The state space model structure is a good choice for quick estimation because it requires only two parameters, namely the model order and one or more input delays.

All these model formulations are solved using iterative optimisation techniques and algorithms like the least squares method. However, this requires a lot of computing power and they are prone to inherent inaccuracies. A much more attractive model formulation is the subspace one which does not need to be solved using iterative optimisation techniques and algorithms, but by only using algebraic calculations [12]. This means the subspace model formulation is a very powerful version of the state-space one that uses only a single-shot solving procedure with improved accuracy.

3. Model calibration and validation

3.1. Experimental procedure – pilot MBR plant and pilot membrane filtration unit

3.1.1. Pilot MBR plant

Both fouling model types have been tested on data obtained from flux stepping tests performed on an Aquabio Ltd. pilot MBR plant located in Worcestershire that treated salad wash water as industrial effluent (see Table 1 below).

3.1.2. Pilot membrane filtration unit

Again both fouling model types have been tested on data obtained from flux stepping tests performed on an ITT Sanitaire Ltd. pilot membrane filtration unit (see Table 2 below). This unit treated tertiary effluent from Cardiff's SBR wastewater treatment plant.

3.2. Model simulation – results for Duclos-Orsello (2006) formulation

3.2.1. Pilot MBR plant - best fit for 5 flux steps at constant TMP/varying flux

Fig. 2 shows the result when fitting the model using the calculated optimal parameter sets for the best five flux steps. The optimal parameter set itself was determined by running a generic genetic algorithm procedure in Matlab©. As can be seen, the model fit is extremely poor when attempting to fit the data from all five flux steps simultaneously.

Table 1
Operational data for pilot MBR plant

Aquabio pilot MBR plant – sidestream crossflow configuration	
Membrane type and area	Vertical "Berghof" tubular; PVC-C 0.02 µm pore size; 4.1 m^2
Membrane data	55 tubes each of 8 mm Ø; outer diameter of module is 90 mm
Feed volume (m^3/h)	10 × ν where crossflow velocity is ν (m/s)
Feed-Permeate differential pressure	−30 … +600 kPa
Pressure drop along module (kPa)	2.1 × ν × l where module length is l (m) = 3010 mm
Backwash/cleaning regime	Automated backflush possible of varying length & duration; periodic hypochlorite clean every few weeks
Biological feed data	COD ~ 700 mgO_2/l; TSS ~ 50 mg/l
Bioreactor operational data	MLSS ~ 7,000 to 12,000 mg/l; SMP ~ 500 mg/l

Table 2
Operational data for pilot membrane filtration unit

ITT Sanitaire membrane filtration unit (without bioreactor)	
Membrane type and area	Horizontal "Kolon" fibres; PVDF 0.1 µm pore size; 20 m^2
Feed flow; permeate flow; backwash	1 to 2.4 m^3/h; 0.6 to 1 m^3/h; 1.2 to 1.8 m^3/h
Backwash interval & duration	Every 4 min with 30s ON
TMP	300 to 500 mbar
Aeration rate	13 Nm^3/h from coarse bubble tube diffuser
Cleaning regime	hypochlorite dosed 4 times daily into permeate tank
Feed flow biological data	COD concentration 50 mgO_2/l; TSS concentration 25 mg/l
Indicative feed flow SMP data	Measured glucose concentration 5 mg/l; measured protein concentration 100 mg/l

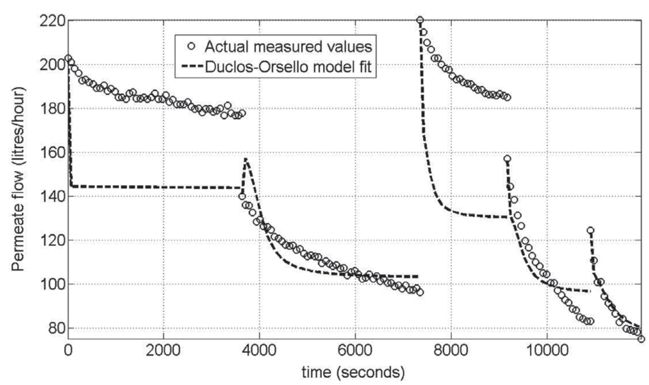

Fig. 2. Pilot MBR plant - best model fit for 5 flux steps.

3.2.2. Pilot MBR plant - best fit for single flux step at constant TMP/varying flux

In a bid to improve the fit, it was assumed that each flux step solution was unique. This could be hypothesised since each flux step with subsequent backwash was actually carried out manually by shutting down the plant, and reversing the flow as necessary whilst also manually altering the membrane module throttle valve setting which itself significantly altered the hydrodynamics occurring within the tubular arrangement. This assumption means that the data set used was actually discontinuous in time between individual flux steps, and therefore each step should be considered separately by the model on a individual data-by-data basis. This altered model optimisation procedure was tried to ascertain if a better fit could be achieved. Fig. 3 is

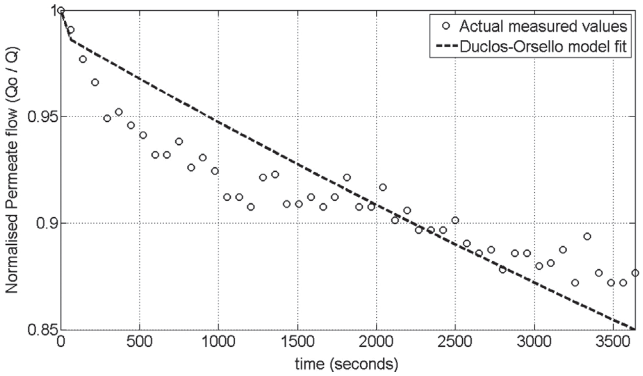

Fig. 3. Pilot MBR plant - best model fit for single flux step.

the result obtained. It is clear that the fit proves very good when flux steps are taken individually as unique solutions. Also the fit improves when the specific step regime produces fluxes and TMPs that are well below critical conditions so that the membrane performance is not compromised.

3.2.3. Pilot membrane filtration unit - best fit for 8 flux steps at constant flux/varying TMP

Fig. 4 shows the result obtained when using the calculated optimal parameter sets for the best eight flux steps for this second pilot unit. The model fit is extremely good which in this case can be attributed to the following reasons:

- The membrane unit has no complex bioreactor (i.e., no significant biological and biochemical variations to be considered).
- Very low mixed liquor concentrations and subsequent very low SMP levels gave a extremely consistent membrane performance.
- The plant flow train is simple, with the entire flux stepping procedure being automated including the backwash procedure.

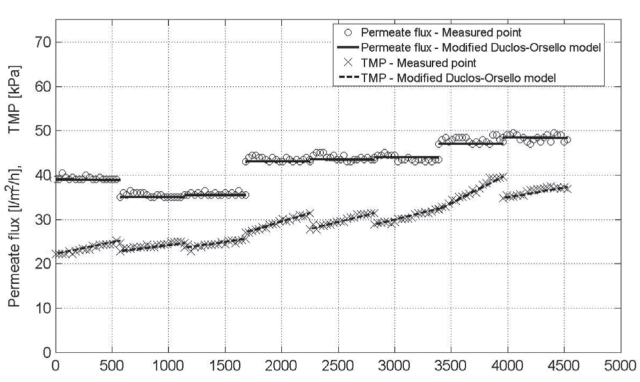

Fig. 4. Pilot membrane filtration unit - best model fit for 8 flux steps.

- Other factors that influenced these exceptional results is this was a constant flux operation giving simpler hydrodynamics with no discontinuities in time between flux steps.
- Also the plant had been operating consistently over a long period of time unlike the Aquabio pilot MBR plant. Further, the flux stepping tests all occurred on the same day, and also the air-sparging procedure used to clean the membrane was at a very high rate (i.e. much higher than for a full size commercial unit) and occurred continuously even during the backwashes. This meant extreme membrane clogging was very unlikely.

In summary, most of the optimised model parameter values are of the same order as stated in the orginal Duclos-Orsello (2006) paper, or for those new parameters created in the modified model they are of a size that make theoretical and mathematical sense. Consequently this model formulation does appear to be accurate enough to be used to model a membrane filtering mixed liquors and experiencing subsequent fouling and clogging events.

3.3. Model simulation – results for IO model formulations

3.3.1. Pilot MBR plant – best fit for 7 flux steps for MISO subspace model

After various assumptions and simplifications of the plant data, the seven best flux steps were used to test the proposed multi-input single output (MISO) model structure. The flow into the membrane module and the generated TMP were used as variables in the input model vector, x, with the permeate flow being the single variable in the output model vector, y. The internal state vectors in this formulation were u and e. When this most simplest of IO model structures is run as a subspace formulation, the best fit is for a 1st order model with an algorithm block size of 13. This fit is carried out by using the last three flux stepping cycles as the validation data set. The best fit subspace model structure was determined as follows:

$$x(t+T_S) = Ax(t) + B\,u(t) + K\,e(t)\,;\, x(0)=0$$
$$y(t) = C\,x(t) + D\,u(t)$$

where the optimised state parameter values are:

$$A = [1.0149]\,;\, B = \begin{bmatrix} -0.0067752 \\ -0.19319 \end{bmatrix};\, C = [-28.133]\,;$$
$$D = \begin{bmatrix} 15.919 \\ 417.98 \end{bmatrix};\, K = [-0.0019766]$$

In this case the best fit achievable is not very good at 55% as shown in Fig. 5. The fit is poor since the model predicts the flux should increase over a flux step cycle when it should actually be decreasing. Thus the model is

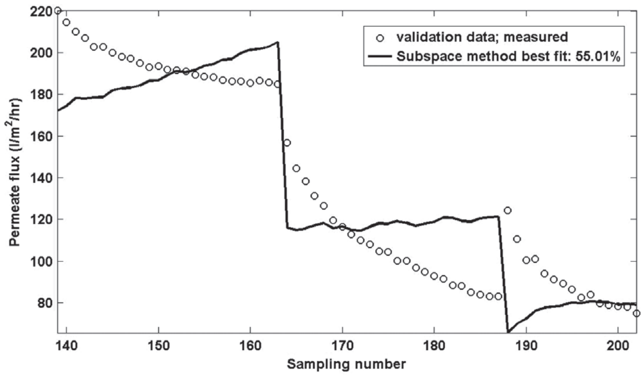

Fig. 5. Pilot MBR plant - best model fit for 7 flux steps (3 for validation) for Subspace method.

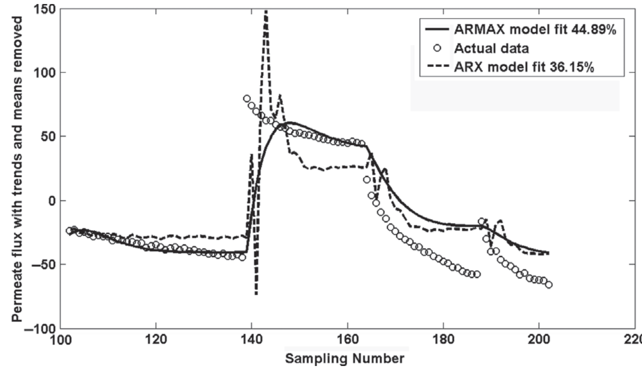

Fig. 6. Pilot MBR plant - best model fit for 7 flux steps (4 for validation) for ARX and ARMAX formulations.

predicting that the membrane fouling reduces over time for the flux step which patently is not true as the pilot plant was not operating at a sufficiently high enough crossflow velocity or low enough mixed liquor concentration to prevent or even reduce cake build up. This obviously suggests that the incoming membrane flow and TMP are not sufficient in themselves to provide a good model fit for a subspace formulation for this particular plant layout.

In a bid to improve the fit using this subspace formulation, then in a similar manner to the previous phenomenological model, a single flux step was tried as a unique solution. In this simulation, part of the single flux data was used for model calibration whilst the remainder was utilised for the validation procedure. The fit for an individual flux step proved very good although for brevity sake the results are not provided here.

3.3.2. Pilot MBR plant – best fit for 7 flux steps for MISO ARX and ARMAX models

Other autoregressive structures were tested using this data set, although this time four steps were used for validation. The best fit MISO ARX model for this particular data set proved to be as follows:

$$A(q)y(t) = B(q)x(t) + e(t)$$

where the optimised state parameter values are:

$$A(q) = 1 - 0.9834q^{-1} + 0.4587q^{-2} - 0.4388q^{-3} + 0.2298q^{-4}$$
$$B_1(q) = -2.369q^{-1} + 8.235q^{-2} - 12.16q^{-3} + 7.262q^{-4}$$
$$B_2(q) = -73.21q^{-1} + 211.6q^{-2} - 348.6q^{-3} + 205q^{-4}$$

Further, the best fit MISO ARMAX model for this particular data set proved to be as follows:

$$A(q)y(t) = B(q)\,x(t) + C(q)e(t)$$

where the optimised state parameter values are:

$$A(q) = 1 - 1.659q^{-1} + 0.6963q^{-2}$$
$$B_1(q) = 0.1388q^{-1} + 0.01811q^{-2}$$
$$B_2(q) = -\,24.46q^{-1} + 23.06q^{-2}$$
$$C(q) = 1 - 0.8898q^{-1} - 0.1102q^{-2}$$

Fig. 6 shows the fits for both these IO model structures. Even though the validation data set in this case is much larger and is half the data available, Fig. 6 shows that the best fits for the ARX and ARMAX model formulations are 36% and 45% respectively, which is slightly worse than the subspace formulation in numerical terms. However, the shape of the fit is very good and in the same general direction. This means as the flux reduces at a slightly decreasing exponential rate due to the gradual switching in membrane blocking mechanisms from rapid pore constriction initially towards a more slower cake build up, the model formulations predict this same effect. This shows this simple MISO model structure for this specific plant layout is capable of predicting the correct direction of permeate flux decrease albeit using autoregressive iterative optimisation methods as opposed to the single shot algebraic subspace methods.

3.3.3. Pilot membrane filtration unit – best fit for 8 flux steps for MISO subspace model

As the plant layout for this unit is very simple with no bioreactor to complicate matters, the selected MISO model structure should give a very high degree of accuracy. In this case the permeate flux, the measured SMP levels, and the measured bulk mixed liquor concentration into the membrane were used as variables in the input model vector, x, with the TMP being the single variable in the output model vector, y. The internal state vectors in the subspace formulation again were u and e. When this MISO model structure is run as a subspace formulation, the best fit is for a 6th order model with an algorithm block size of 4. This fit is carried out by using the last four flux stepping cycles as the validation

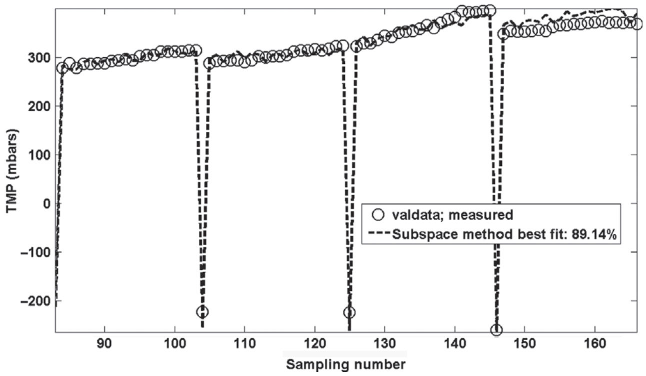

Fig. 7. Pilot membrane filtration unit - best model fit for 8 flux steps (4 for validation) for Subspace method.

data set. For simplicities sake, the subspace model equations are not given here. The result as shown in Fig. 7, depicts an excellent fit amounting to 89.14%. The shape of the fit is extremely good and is in the right direction (i.e. TMP increases with time), thus validating the use of additional input biochemical data (e.g. SMP levels) to improve the overall model fit.

3.3.4. Pilot membrane filtration unit – best fit for 8 flux steps for MISO normal state-space model

As before other autoregressive structures were tested using this data set with again four steps used for validation. It was found that the ARX and ARMAX formulations did not give usable results. Only the standard state-space formulation (whose equations are not given here for the sake of brevity) gave a workable fit, albeit not a very good one of 8.5% as shown in Fig. 8. This simulation run reveals that there is a deterioration in fit with only one method providing a positive solution (i.e., the state-space method). However, the shape and direction of the fit is correct this time even though the simulated data is prone to gradually attenuating fluctuations around a mean point (i.e. rapid but diminishing oscillations). These poor fits can be attributed to the regular backwash events that cause a sudden large negative drop in the TMP that the simulated models are unable to cope with. For these methods, it is clear that the data represents a different class of models from those utilised by the standard autoregressive methods. It can be concluded from all these simulations, that increased input data sets do not necessarily improve a model fit but they can greatly improve the shape and direction of the fit.

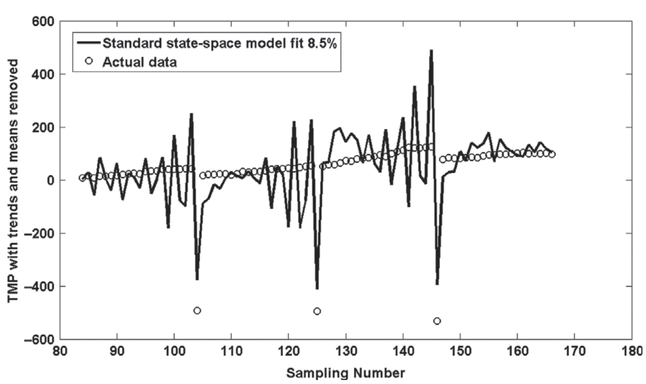

Fig. 8. Pilot membrane filtration unit - best model fit for 8 flux steps (4 for validation) for standard state-space formulation.

4. Conclusion

Table 3 summarises qualitatively the simulation results for both model types. Overall it is clear that the phenomenological model performed very well especially for constant flux/varying TMP operation. Conversely, only the subspace method gave consistent results for the IO models used, although not always, with the ARMAX formulation proving next best.

It initially looks like this novel approach has many advantages over traditional mechanistic models while giving comparable results for some IO structures. It even has many advantages over other more traditional non-mechanistic models such as ANN and FNN methods. Early simulation results described in this study prove this, especially for subspace methods. However these methods can prove very fragile particularly the ARMAX formulation which is prone to crashing. Additionally a comprehensive "model conceptualisation procedure" is required to tie it into reality which needs expert know-how to set up. They also require very large data sets to produce accurate formulations, and these linear models are only useful around a very narrow operating range or operating point. Non-linear model versions can improve the predictive accuracy but are even more fragile.

In conclusion, it may prove advantageous to use these methods for model prediction under most circumstances apart from the following instances:

- Not for design of new plant (particularly for processes with long time constants), and the biological operation of plant (i.e., off-line measurements).
- No good as research tools to investigate membrane fouling. Cannot predict one-off fouling events, only generalised scenarios.

The situation in which they may particularly prove themselves superior to traditional model structures, is for model predictive control (possibly in real time) for processes with very short time constants (i.e. rapidly changing flux/TMP data). However they would need constant automated updating of historical data sets using on-line sensors. In conclusion further research

Table 3
Summary of results of both model types

Results from data	Phenomenological model	Miso models			
	Duclos-Orsello	Subspace	ARX	ARMAX	State-space
Pilot MBR plant – flux stepping individual	Very good fit	Reasonable fit	–	–	–
Pilot MBR plant – flux stepping multiple	Poor fit	Poor shape fit	Poor fit	Reasonable shape fit	No fit
Pilot membrane unit – flux stepping multiple	Excellent fit	Excellent fit	Poor fit	Poor fit	Fair shape fit

is required using longer historical data sets to definitively ascertain whether this autoregressive modelling approach can be further developed and improved upon.

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Symbols

A_b — Area of membrane blocked by foulant (m^2)
$A_{0(bw)}$ — Area of membrane blocked by foulant following backwash interval (m^2)
A_u — Area of unblocked membrane (m^2)
C_b — Bulk concentration of mixed liquor (mg/l)
f' — Fractional amount of total foulant contributing to deposit growth
J_0 — Initial flux rate of clean membrane (m/s)
J_b — Filtrate flux within the blocked area (m/s)
J_u — Filtrate flux within the unblocked (m/s)
k_b — blocked area reset constant (following backwash)
k_p — membrane surface scour constant
Q — Volumetric flow rate (m^3/s)
R_{inb} — Resistance of the membrane and the resistance caused by pore constriction (m^{-1})
R_m — Resistance of the clean membrane (m^{-1})
R_p — Resistance of the deposit (m^{-1})
R' — Specific protein layer resistance (m/kg)
S_{smp} — Soluble microbial product (SMP) concentration (mg/l)
t — Filtration time (s)
TMP — Trans-membrane pressure (Pa/bar)

Greek letters

α — Pore blockage parameter (m^2/kg)
β — Pore constriction parameter (kg)
μ — Viscosity (kg/m3)

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