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Dynamic multidimensional modelling of submerged membrane bioreactor fouling

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ABSTRACT

Existing membrane fouling models are limited to simple hydraulic profiles which is a limitation particularly for planar membranes. Here, we present a new model that allows for a distributed shear profile, with dynamic linking of flux and transmembrane pressure (TMP). Shear profile is calculated using a multi-phase computational fluid dynamic approach, and is applied to a distributed parameter model to simulate membrane fouling profile and flux distribution. This allows for simulation of complex flux-step experiments, or situations where non-uniform shear is present. The model was applied to filtration experiments conducted in a pilot-scale anaerobic membrane bioreactor treating slaughterhouse wastewater comprising 1950 ± 250 mg/L total solids and was able to effectively fit experiments under dynamic critical flux conditions. Cake compressibility was a key parameter, and was estimated at 870 ± 80 Pa. Non-uniform gas distribution decreased critical flux from 12 LMH to 8.5 LMH. This emphasises the importance of local flow conditions on membrane fouling behaviour and that performance can depend heavily on reactor configuration and hydraulics.

1. Introduction

Submerged membrane bioreactors (SMBRs) are an established alternative to conventional clarifier based wastewater treatment technology with a number of advantages [1]. These include the removal of a separate clarification step and hence reduced footprint, better control over solids inventory and solids retention time, a more concentrated biomass and hence a higher space loading rate, and improved effluent quality due to elimination of solids through the membrane. Disadvantages are largely energy consumption related to membrane fouling management and permeate collection. The high cost of membranes and their replacement; which can be 50% of total capital expenditure [1], as well as energetic and chemical costs of fouling control and cleaning, provides strong motivation to predict and manage membrane fouling effectively.

Membrane fouling is the accumulation of largely insoluble material on or within the membrane [2], reducing membrane flux at a given transmembrane pressure (TMP) or conversely, increasing TMP at a given flux. It is possible to control membrane fouling during operation by gas sparging to create shear across the membrane and thus remove foulant. Physical and chemical cleaning operations are also used to periodically clean membranes, but require an interruption to process operation and are therefore less desired.

Membrane life can be enhanced by operating the SMBR below its ‘critical flux’; or the flux below which resistance to flow is governed by inherent membrane, rather than cake resistance [2]. Critical flux is generally determined in flux-step experiments, where membrane flux is step-wise increased and the corresponding TMP continuously measured [1,3]. Critical flux is assessed as the flux at which the fouling rate (or rate of TMP increase, dP/dt) increases substantially above the baseline [4]. Overall resistance to flux is dominated by membrane resistance at subcritical flux and controlled by the resistance of the fouling layer at supercritical flux. Therefore, operation of an MBR below its critical flux is inherently more stable, with minimal periodic cake removal required (e.g. through backflushing). Critical flux is influenced by membrane shear, membrane properties, solids properties and membrane configuration [2]. It is therefore important to predict membrane and cake formation behaviour under subcritical, supercritical, and in transition fluxes.

Membrane fouling in MBRs is most commonly assessed via experimental analysis [5]. This faces a number of challenges:

(1) The outcomes of a flux-step analysis are generally only applicable to MBR setups and process conditions similar to those tested in the experiment. In particular, lab-scale studies

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Abbreviations: MBR, membrane bioreactor; AnMBR, anaerobic MBR; SMBR, submerged MBR; TMP, transmembrane pressure; CFD, computational fluid dynamics; TS, total solids

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have limited applicability to full-scale applications due to different hydrodynamics [5].

(2) Hydrodynamics around the membrane creates surface shear on the membrane responsible for fouling control. Techniques for hydrodynamic characterisation include the use of dye particles [4,6,7], flow velocimetry [4,8] and particle image velocimetry [9,10]. These techniques however, cannot easily be implemented in large scale systems that have large volumes, variable flows and opaque fluids. They are also intrusive to flow and often restricted by the lack of space in reactor systems [11].

(3) Experimental analysis is generally limited to studying the impact of a small number of process variables at a given time and therefore may fail to account for the combined effects or interactions of the many process factors that affect membrane fouling [5]. These include sludge properties such as solids concentration, stickiness, floc size, compressibility of cake layer and viscosity; and process parameters such as membrane flux, applied TMP and gas sparging intensity; which can vary between systems and over time.

Therefore, model based analysis is an important tool for fouling characterisation and effective fouling control, which allows for determination of platform independent fouling characteristics and a better fundamental understanding of controlling mechanisms.

Deterministic modelling of membrane fouling is at a comparatively early stage compared to general wastewater process and hydrodynamic modelling, partly due to its complexity. The default model approach is the use of lumped (non-distributed) parameter models which sufficiently characterise simple fouling behaviour [12–14]. These models however, are inapplicable in membranes with non-uniform shear and cake distributions and provide limited insight into transitionary behaviour from satisfactory to unsatisfactory performance. A fractal permeation model was proposed by Meng et al. [15] which estimates cake layer permeability by using the fractal theory to characterise its microstructure. This model however has limited use as a predictive model as it is unable to estimate the impact of changing operational parameters and reactor conditions on cake resistance. Li and Wang [16] developed a semi-analytic, sectional resistance-in-series (RIS) fouling model which can be used to simulate dynamic sludge film formation on the membrane and its effect on TMP. This model considers net cake accumulation on the membrane to be dependent on the balance between accumulation due to membrane flux, which encourages solids deposition, and detachment due to shearing. This model can predict flux, cake thickness, for a given transmembrane pressure and bulk liquid shear, on the basis of parameters such as membrane resistance, solids stickiness and compressibility. Further expansions and modifications to the model have since been made: Wu et al. [17] included the effect of variable particle size solids, Zarragoitia-Gonzalez et al. [18] integrated the model with the Activated Sludge Model No.1 (ASM1) to predict the impact of biologically produced soluble and insoluble products on membrane fouling and Mannina et al. [19] further included the deep bed filtration theory to predict COD removal by the accumulated cake layer.

The sectional RIS fouling model and its extensions still have a number of limitations:

(a) The model geometry is 1-D and hence cannot assess the impact of variable shear and non-uniform fouling across the membrane surface.

(b) Maximum shear intensity is correlated with aeration intensity via an empirical laminar correlation, and is therefore inaccurate for the prediction of shear in generally turbulent conditions. Shear profile along membrane length is also approximated by a sine function rather than a deterministic shear profile.

(c) The flux–pressure interaction is solved by iteration of the differential equation solution at a defined time point. This does not allow dynamic analysis of the flux–pressure interaction.

In particular, interaction of these limitations does not allow for detailed analysis of the interaction of fouling and flux distribution across a broader permeable domain.

In this study, we provide a new approach to fouling modelling for a two dimensional membrane domain with shear calculated by a three dimensional, multiphase computational fluid dynamics (CFD) model. Pressure and flux are dynamically linked to resolve flux distribution across the domain and enable overall flux to be fixed.

2. Model overview

Fig. 1 provides an overview of the modelling approach. A three dimensional and two phase (gas–liquid) CFD simulation of the anaerobic MBR (AnMBR) configuration was used to estimate shear distribution on the membrane surface. This was then used with the fouling model of Li and Wang [16] to predict dynamic cake formation on the membrane. During a simulation, pressure is dynamically controlled using an integral controller such that the overall flux matches desired flux. Flux can be manipulated dynamically, which enables this model to simulate flux-step experiments for the prediction of critical flux for various operating parameters or normal subcritical operation.

2.1. CFD model prediction of membrane shear

A two fluid (Eulerian–Eulerian) approach was used to simultaneously model liquid and gas phases. The sludge mixture was treated as a homogenous single phase with a non-Newtonian rheology.

A rheological model was based on AnMBR sludge after 30 days batch operation at 33 °C [20], which is similar to the system studied in this analysis (52–65 days operation at 34 °C). The study found that the Bingham model best describes sludge rheology at intermediate shear rates (500–800 s^{-1}). The corresponding correlation Eq. (1) that relates sludge viscosity with total solids (TS) concentration is valid for TS concentrations between 1.2 and 22.3 g/L and at a temperature of 22 °C.

$$\mu = 0.001e^{0.04TS} \tag{1}$$

Viscosity obtained from the above correlation was adjusted for a temperature of 34 °C using an Arrhenius relationship [21], $\mu_{T34}/\mu_{T22} = \theta^{(34-22)}$ (temperature correction coefficient, $\theta = 0.98$, obtained from a water viscosity vs. temperature relationship). Therefore, at a TS concentration of 2 kg/m^3 and a temperature of 34 °C, viscosity was estimated to be 0.0008 Pa s.

Fluid turbulence was modelled using a $k-\varepsilon$ turbulence model, which is the most widely validated of the existing Reynolds Stress turbulence models [22,23]. Default values of the empirical turbulence constants are used in the CFD analysis, as described by the ANSYS CFX manual which is in accordance with the standard values provided by Rodi [22]. Additional models include the use of a Grace drag model for gas–liquid momentum transfer, Tomiyama lift force model and Sato's model for turbulence enhancement in bubbly flows.

The AnMBR domain was meshed using ANSYS meshing software. The mesh comprises a total approximately 2.7 million elements and is within quality recommendations (orthogonal quality >0.1, skewness <0.95). The solver was run in transient mode with timesteps of 0.01 s for a total duration of 120 s or until the model reached steady state; i.e. no variation in monitored parameters