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DRFM hybrid model to optimize energy performance of pre-treatment depth filters in desalination facilities

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Abstract

Rapid depth filtration is the dominant pre-treatment technology in seawater desalination industry today. Optimizing the pre-treatment filter's energy performance provides economies of scale in the total energy usage of desalination facilities on a broader sense. However, this objective remains difficult to achieve by far. In this study, we develop a numerical algorithm, termed as Dynamical Rapid Filtration Model (DRFM), to simulate the effective clogging dynamics occurring within a depth filter which depends on a multitude of controlled and non-controlled operating parameters. DRFM quantifies the filtration kinetics with a modified Yao's model to represent the particle removal mechanisms occurring within the simulated filter. A unique length scale is also introduced to account for the particle size effect on the filter's energy loss rate incurred, i.e. its energy performance, during its effective filtration stage. Concurrently, we performed an experimental study with a lab-scale depth filter to develop a model equation for measuring its total contaminant mass removal rate (R_c) during effective clogging conditions. For a predicted R_c transient profile, good agreement is obtained between the experimental results and predicted values from DRFM. We then extensively discuss on a novel DRFM hybrid model to optimize the filter's energy performance which subsequently affects the filter's optimized backwashing timing for achieving economies of scale. The simulation results from the hybrid model demonstrates on how various filter configurations can result in lower energy cost to pre-treat each unit volume of intake seawater as compared to the current industrial average of $0.39\text{kwh}/\text{m}^3$. Finally, we include a cost analysis to demonstrate on how the obtained economies of scale alleviates a portion of the total energy cost for each unit volume of desalinated water.

The short version of the paper was presented at WES-CUE2017, Jul 19-21, Singapore. This paper is a substantial extension of the short version of the conference paper.

Keywords: granular pre-treatment rapid filtration; energy performance; economies of scale; backwashing optimization; water-energy nexus

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Highlights

- DRFM predicts filter's energy loss rate values due to effective clogging
- DRFM hybrid model optimizes filter's energy performance a priori
- Simulated filter's energy cost lower than the current industrial value of $0.39\text{kwh}/\text{m}^3$
- Iterative approach estimates optimal timing to backwash the clogged filters
- Economies of scale generally reduces the unit energy cost of desalinated water

Graphical abstract

1. Introduction

1.1. Background

At present, the number of desalination plants stands at 18,426 providing an approximate 86.8 million cubic metres of desalinated water per day to more than 300 million people globally (IDA, 2018). Substantial amount of energy is usually consumed by the multiple treatment steps deployed within a typical medium- or large-scale seawater reverse osmosis (SWRO) desalination plant (see Figure A supplementary) which contributes to climate change (Facchini et al., 2017). Studies have also confirmed that each unit volume of desalinated water consumes the most energy among other potable water producing technologies (Voutchkov, 2018). Currently, the average total energy usage for desalinated water is $3.10 \text{ Kwh}/\text{m}^3$ and the average unit cost is $\$1.1 \text{ USD}/\text{m}^3$. The total energy usage/cost is generally distributed directly and indirectly among the multiple treatment steps in desalination facilities. For example, energy is utilized to produce chemicals for use during the pre- and post-treatment steps (indirect energy), and to manage the produced sludge subsequently (direct energy). On the other hand, the RO treatment step contributes most directly to the total energy usage (Wakeel et al., 2016; Voutchkov, 2018). This intricate relationship between the desalinated water produced and the required energy usage can broadly be defined as water-energy nexus (Dubreuil et al., 2013; Wakeel et al., 2016; Lee et al., 2017).

To ensure that desalinated water remains affordable to an increasing urban population, optimization of the different treatment systems in desalination facilities is desirable to minimize the expected growth rate in the total energy cost. For example, desalination technology using renewable energy has been studied (Ghaffour et al., 2014; Gude, 2015; Gonzalez et al., 2017). While the desalination technology continues to be innovated to achieve optimization, limitations may arise due to thermodynamics consideration. Hence, optimizing the other treatment technologies (pre- and post-treatment) deployed in desalination facilities becomes necessary (Elimelech and Philip, 2011; Wakeel et al., 2016) as they also contribute to the total energy cost as discussed. In this paper, the focus is on the pre-treatment depth filtration technology which is deployed to remove turbidity particles for mitigating particulate fouling in the downstream RO operating membranes (Voutchkov, 2012

and 2017a). Many medium- and large-scale desalination facilities today are still deploying this pre-treatment technology. An example is the current largest facility located in Sorek, Israel which operates at $624,000\text{m}^3/\text{d}$ (Water Technology, 2016). Generally, the pre-treatment step is the second-largest energy consumer, at around $0.39\text{ Kwh}/\text{m}^3$ on average (Voutchkov, 2018), among the other treatment steps in desalination facilities (Elimelech and Philip, 2011; Zarzo and Prats, 2018).

Recent studies have underlined that the volume capacity treated by rapid gravity filters provides economies of scale in the energy intensity of water treatment facilities (Molinos-Senante and Sala-Garrido, 2017). Directly, it indicates that extended production rate from the operating filters is effective to gradually offset a portion of the treatment plant's total energy cost. This aligns with the optimization objective of pre-treatment depth filters in desalination facilities which is to maximise the production rate of quality effluents into the downstream RO membranes before the filters' energy loss rate due to effective clogging conditions reaches their pre-defined allowable value. Generally, this energy loss rate parameter indicates the optimization level in the filter's energy performance occurring on a broader sense. We hypothesize that the latter is optimized if the former parameter is best minimized during effective clogging conditions. The filter's energy loss rate occurring is directly affected by several controlled and uncontrolled operating parameters which are related to the intake seawater quality and the filter's changing media characteristics due to effective clogging. We also add that lowering the average energy cost required to pre-treat per unit volume of intake seawater too contribute to the optimization of the filter's energy performance.

At present, optimizing the filter's energy performance is difficult as modelling the hybrid relationship between the filter's effective filtration stage and its energy loss rate occurring requires further attention. Consequently, practitioners are still experiencing problems estimating the optimized timing to backwash the clogged filters (maintenance phase) a priori with respect to the energy loss rate criterion. For example, in case studies such as the Doha Research Plant (Ebrahim et al., 2001), Jeddah SWRO plant (Al-Sheikh, 1997) and Addur SWRO plant in the Middle East (Prihasto et al., 2009), filters' maintenance was carried out due to unexpected exceedance in either the effluent turbidity concentration or maximum allowable

energy loss rate. This scenario often occurred during the pre-treatment rapid filtration of influents having turbidity values greater than 20 – 50 *NTU* (WHO, 2006). On the contrary, the current practice in the industry calls for filters' maintenance once at every 24 to 48*h* under normal operating conditions (MWH, 2005; Voutchkov, 2010, 2012, 2017a). Hence, it is unlikely that economies of scale are achieved at this moment as the pre-treatment filters may still operate for an extended period, especially if the intake seawater quality is good which usually results in low energy loss rate occurring.

Filters' backwashing is typically carried out by mechanically pumping volumes of filtered effluent or brine water in a reverse manner into the filter which then expands the interior media depth and flush away the unwanted materials (resulting in backwash waste). Additional air scouring may also be necessary for filter media having effective sizes less than 0.8*mm* (Voutchkov, 2017a). Each backwash cycle typically lasts about 30*min* and consumes about 2~6% of the total volume of filtered effluent under normal operating conditions. On the contrary, the backwashing cycle shortens to every 2 to 6*h* during the operational filtration of high-turbid influents and consume more than 5% of filtered effluent during each time (Voutchkov, 2012, 2017a).

Besides the use of filtered effluent, the backwashing operation employs chemicals to further treat the produced backwash waste before proper disposal or recycling it back to the main influent line of the desalination plant. On average, the chemical cost for pre-treatment in desalination facilities is 0.05 *USD/m³* as depending on the location of the plant site, availability of chemicals etc. (Voutchkov, 2012). By conducting a cost analysis (see Table A supplementary) using documented values from the literature (Voutchkov, 2012; Water Technology, 2016), we underline the chemical costs incurred by large-scale desalination facilities to treat the backwash wastes generated. It can be assumed that the above-stated chemical cost has already comprised of the indirect energy cost for chemicals production. In addition, the produced sludge after treatment of the backwash waste can be environmentally damaging if not managed properly (Miller et al., 2015). Proper sludge management (dewatering, transport, incineration etc.) also contributes to carbon emissions and additional energy costs (Gu et al., 2016, 2017). This is further highlighted by the

general disposal costs for handling the produced sludge from the treatment of the backwash waste in large-scale desalination plants (Table A supplementary). At present, the average energy usage during sludge management in desalination facilities is 0.27 Kwh/m^3 (Voutchkov, 2018).

In summary, optimizing the filter's energy performance is highly desirable as it enables the pre-treatment depth filters to operate effectively for extended periods before appropriate maintenance which then provide economies of scale. By building on the recent findings of Molinos-Senante and Sala-Garrido (2017), we believe that the total energy cost incurred by desalination facilities can also be alleviated to an extent if the pre-treatment filters appropriately provide the economies of scale benefit. To do so, we need to effectively model the hybrid relationship between the filter's effective clogging stage and its energy loss rate occurring. The hybrid model will then be useful to estimate the optimized timing to backwash the clogged filters based on the energy loss rate criterion. Furthermore, the model must be made convenient and practical to practitioners. To the best of our knowledge, we are not aware of such available model at this moment. To justify our statement made, we conduct an extensive literature review to delineate the previous works done in modelling the clogging dynamics occurring during depth filtration and the filter's associated energy loss rate as indicative of its energy performance.

1.2. Literature review

Starting with experimental analysis, Iwasaki (1937) and Mints (1966) are several of the pioneers for highlighting the significance of sand filtration process for water purification. Ives (1970) extensively discussed on the different particle removal mechanisms involved during rapid filtration, as built from the works of Ison and Ives (1968), to quantify the filter's performance. The notable Yao's filtration model (Yao and O' Melia, 1968; Yao et al., 1971) was subsequently developed to consider the particle movement, via sedimentation, interception and molecular diffusion solely, along the streamlines around a singular collector grain. Another notable modelling study was by Adin and Rebhun (1977) which established the filtration kinetics equations from the fluid momentum and mass continuity equations, including the

detachment mechanism. O'Melia and Ali (1978) then further modified the Yao's model to approximate the energy loss rate occurring during clogging conditions, by assuming that the trapped particles serve as additional collectors to improve the filter's performance.

O'Melia and Ali model (1978) was subsequently modified by other researchers to model the particle size effect on the filter's energy loss rate during effective filtration. Readers are referred to the following references (Mackie and Bai, 1991; Darby et al., 1992; Boller and Kavanaugh, 1992; Veerapaneni et al., 1993, 1997; Tobiasson and Vigneswaran, 1994; Wiesner, 1999) for further details. Till now, the quantitative understanding of the particle size effect on the filter's energy loss rate due to effective clogging conditions remains limited. Mays and Hunt (2005, 2007) notably improved on O'Melia and Ali model with further calibration from 43 previous sets of highly controlled laboratory results. Their resulting model predicts the filter's energy loss due to clogging by montmorillonite. Besides the particle size effect, investigations of other operating parameters which include media size, hydraulic loading rate, particle concentration etc., have also been carried out (Kau and Lawler, 1995; Stevenson, 1997; Williams et al., 2007; Han et al., 2009; Kim and Lawler., 2012; Bennacer et al., 2013; Alem et al., 2015). At the same time, we note that these studies only considered the filtration of low turbid influents, likewise in earlier studies (Ives and Pienvichitr, 1965), and their validity for high-turbid influents has not been verified. By far, we are not aware of any available experimental model which predicts the filter's breakthrough time, i.e. timing for maintenance, by using the known operating parameters.

Computational tools have been advanced to simulate the clogging dynamics occurring within an idealized filter geometry (both 2D and 3D). For example, the Eulerian-Lagrangian (EL) approach first resolves the moving fluid distribution in the Eulerian framework within the numerical domain before simulating the Lagrangian particle movement along the fluid streamlines. In Open Field Operation and Manipulation (The OpenFOAM Foundation), which is an open-source computational fluid dynamics (CFD) software, the track-to-face algorithm is adopted to simulate the Lagrangian particle movement from one computational grid to the other. The algorithm requires that the size of the Lagrangian particle to be smaller than the

smallest length of the computational grid itself. Thus, to simulate the movement of larger Lagrangian particles of $O(10^{-5} m)$ within the pore-space of a single collector grain having the typical size of $O(10^{-4} m)$, the maximum allowable number of computational grids in each axial direction is around $O(10^1)$ which then affects the accuracy of the fluid flow distribution computations. On the contrary, for much smaller Lagrangian particles of $O(10^{-7} m)$, the number of grids in each axial direction exceeds $O(10^3)$, resulting in billions of grids for a full three-dimensional (3D) problem which is computationally very expensive which thus requires the integration of parallel computing technique (Resutek, 2016). Hence, predictive capability for a full-scale operating filter is difficult.

The use of commercial CFD tools is also appealing to practitioners due to the relative ease of use and friendly user interfaces (Tung et al., 2004; Hassan et al., 2013). However, the difficulty of simulating the clogging behaviour of the entire filter system, i.e. computation for the full mesh of collector grains and their complicated pore structures, remains a huge challenge due to the large amount of computing resources required. Examples include coupling of CFD with the discrete element method (DEM) by Jajcevic et al. (2013) using a GPU-based computer architecture to simulate 25 million particles in a fluidized granular system and pore-scale simulations of porous-media systems (Raeini et al., 2012; Muljadi et al., 2015) which are usually computationally expensive.

The Lattice Boltzmann Method (LBM) is also common to simulate the filter's clogging dynamics. For example, Long and Hilpert (2009) developed a new correlation for the diffusion mechanism with LBM to quantify the filter's removal performance of both small and large particles. A recent LBM work by Abdelhamid and El Shamy (2016) involved the pore-scale simulation of the migration of fine particles to further improve the design of granular filters. While the computational novelty must be acknowledged, we note that these models are more likely to advance the general understanding of the filter's clogging behaviour and are not able to perform the predictions to achieve the optimization objective as outlined in this study. The use of traditional numerical methods has also been attempted to simulate other types of porous-media systems which include contaminant transport in groundwater systems (Assumaning et al., 2012) and virus transport in fractured porous media (Ojha et al.,

2011). In summary, while computational tools are effective to advance our general understanding of the filter's clogging dynamics, we underline that the computational cost remains difficult for practitioners to efficiently perform large variations to the filter-related parameters. The computing expertise involved may also be a hindrance for industrial applicability.

Theoretical analysis provides another alternative by coupling the homogenization upscaling approach with the multi-scale perturbation technique to reduce the complexity of the macroscopic problem. It does so by averaging the microscale variations while retaining the important properties of the macroscopic behaviour. This approach requires the use of a periodic prescribed microstructure and sufficiently small dimensionless scales to relate the macroscale and microscale variations. Empiricism is minimized by rigorously handling the governing equations involved. This approach has since been adopted to model the filter's clogging behaviour.

Battiato and Tartakovsky (2011) and Korneev and Battiato (2016) developed macroscopic models which quantify the reactive transport occurring in porous media (including polydisperse media). Their models enable one to derive the suitable effective homogenized equation for varying Peclet and Damköhler numbers. Most recently, Dalwadi et al. (2015) extended on the homogenization theory to quantify the effectiveness of a decreasing porosity gradient to maximise a filter's trapping capability. They later consider the changes to the microscale media properties to quantify the filter blockage over time (Dalwadi et al., 2016). While the theoretical novelty is notable, their analysis have yet to be extended to industrial operating conditions. This remains an open research problem.

1.3. Scope and objective of study

In this study, we develop a numerical algorithm, termed as Dynamical Rapid Filtration Model (DRFM), to explicitly simulate the spatiotemporal variations to the filter-related properties as effective clogging occurs and to predict the filter's energy loss rate with the known operating parameters. DRFM also aims to provide relative ease to practitioners in altering the computer algorithm with the C++ computer language and minimize the computational resource required for each simulation run.

Concurrently, we performed an experimental study with a lab-scale granular filter to measure the filter's total contaminant mass removal rate (R_c), with an emphasis on high-turbid influents to address the earlier discussed problems experienced by practitioners. A model equation was subsequently developed with the obtained experimental data which approximates the filter's R_c transient profile under varying operating conditions. The experimental results were later found to agree well with the predictions from DRFM and the R_c model equation, which result in a proposed hybrid model to pre-determine the filters' configurations (controlled parameters) for optimizing their energy performance during effective clogging conditions. An iterative method is subsequently developed from the hybrid model to predict the optimized timing to backwash the clogged filters to achieve economies of scale. Finally, we perform a cost analysis to demonstrate on how the obtained economies of scale alleviate a portion of the total energy cost for each unit volume of desalinated water.

In the following, we first describe the model development of both DRFM and R_c equation in Section 2. The general computational structure employed in DRFM is given in Section 3. The conducted experimental study is then described in Section 4. Model validations are then carried out in Section 5, together with extensive discussions of the DRFM hybrid model to pre-determine the filters' configuration for optimizing their energy performance during effective clogging conditions. An iterative method is then introduced to approximate the optimized timing to backwash the clogged filters, followed by a cost-analysis to demonstrate the economies of scale benefit on a broader sense. Finally, we conclude with an overview of our completed works in Section 6.

2. Model development

2.1. Dynamical Rapid Filtration Model (DRFM)

DRFM represents the depth removal of turbidity particles within a granular filter by the transient growth of the granular media's effective size following the volume conservation principle. This growth is expected to be inhomogeneous along the depth of the media (from top to bottom), whereby the bulk volume of turbidity

particles will be effectively removed within its upper compartments which results in larger media grains in this region over time. For generality, readers are referred to Table 1 for the descriptions of the different particle removal mechanisms involved within a granular filter. DRFM assumes a modified Yao's model (Yao and O' Melia, 1968; Yao et al., 1971) by considering the changing effects of the media properties on the filter's performance. The removal mechanisms of interception and gravitational sedimentation establish the focus of DRFM, whereby both the straining and inertial impaction mechanisms are assumed to lump with interception.

During pre-treatment rapid filtration, the turbidity particles removed within the filter are typically within the reported size range of 20 to 100 μ m or larger (Tehowater, 2017) as the downstream cartridge filters are usually built to remove this particle size range or smaller. Hence, both diffusion and electrostatic attraction mechanisms are neglected for rapid filtration considerations. A unique length scale between the respective sizes of a singular media grain and a trapped turbidity particle is proposed to account for the particle size effect on the filter's energy performance (energy loss rate) under effective clogging conditions. To the best of our knowledge, this empirical ratio has not been introduced before in previous related works.

We summarize DRFM's computational procedures in pseudo-algorithm 1 below. More details about DRFM's workflow will be provided in Section 3. Finally, readers are referred to Supplementary A for the exact details and descriptions of the governing equations adopted in DRFM.

Pseudo-algorithm 1

- I. User to input the seawater quality conditions $(c_0, V_s, \rho_p, \mu_{in}, d_p)$ and initial media properties of the filter $(\varepsilon_0, L_m, d_{c,0})$
- II. User to input total effective filtration period (t_{total}) and associated time-step (Δt)
- III. User to input discretization step (Δz) for L_m to determine the number of nodes (n) in the numerical domain
- IV. From $t = \Delta t$ till t_{total} , DRFM performs the following computational steps for all nodes at each Δt step
 - a. Compute $D_{c\%}(z, t)$ in (A4, supplementary) by using computed $c(z, t - \Delta t)$ from previous time-step

- b. Compute $\varepsilon_c(z, t)$ in (A5, supplementary) and $d_c(z, t)$ in (A6, supplementary) by using computed $D_{c\%}(z, t)$ from step (a)
 - c. Compute $\eta_I(z, t)$ in (A7-a, supplementary) by using $d_c(z, t)$ from step (b), and compute η_G in (A7-b, supplementary)
 - d. Compute $\eta_c(z, t)$ in (A8, supplementary) as the sum of $\eta_I(z, t)$ and η_G from step (c)
 - e. Compute $\lambda_c(z, t)$ in (A9, supplementary) by using $\varepsilon_c(z, t)$, $d_c(z, t)$ and $\eta_c(z, t)$ from (A5, supplementary), (A6, supplementary) and (A8, supplementary) respectively at the current time-step
 - f. Compute $c(z, t)$ in (A10, supplementary) by using computed $\lambda_c(z, t)$ from step (e)
 - g. Compute $\alpha(z, t)$ and $\alpha'(z, t)$ in (A11, supplementary) under clogging conditions by using computed $\varepsilon_c(z, t)$ and $d_c(z, t)$ from step (b), with the inclusion of θ'_A from (A12, supplementary)
-

The input model parameters from Step (I) in pseudo-algorithm 1 can be classified into controlled ($V_s, \mu_{in}, d_p, L_m, d_{c,0}$) and non-controlled parameters (c_0, ρ_p). It is also worth noting that $d_{c,0}$ directly affects ε_0 while μ_{in} is mainly affected by the filter's operating temperature. These parameters affect the filter's energy performance occurring during effective clogging conditions. The remaining assumptions in DRFM's algorithm are outlined in the following to facilitate predictions with DRFM.

- Average diameter of turbidity particle (d_p) is quantified by the dominant particle size within the influent source, i.e. large polydispersity in the particle size range is currently not considered
- Exceedance in the energy loss rate (exceedance in filter's energy performance) occurs due to effective clogging before exceedance in the effluent concentration

2.2. Mathematical representation of filter's performance

Let R_c be the particle removal constant incurred during the effective filtration of the influent's turbidity particles. To compute the R_c transient profile, we first adhere to the continuity equation in its generalized vector notation in (2.1) (Krantz, 2012) which neglects the diffusion mechanism.

$$\frac{\partial c}{\partial t} + \nabla \cdot c \vec{u} = \hat{G} \quad (2.1)$$

where c is again the concentration but expressed in the form of molar density here, $\vec{u}$ the molar-averaged velocity vector, $\hat{G}$ the total molar generation rate per unit volume and t is time.

We again assume unidirectional flow within the filter and further simplify (2.1) into (2.2) by adopting the following: (a) regarding c as mass concentration of particles as before, (b) replacing $\vec{u}$ by a constant V_s superficial velocity which advects the influent particles in the ballistic z -direction, and (c) replacing $\hat{G}$ by $-R_c$ which is defined as the total mass removal rate of the turbidity particles per unit volume of fluid within the filter.

$$\frac{\partial c}{\partial t} + V_s \cdot \frac{\partial c}{\partial z} = -R_c \quad (2.2)$$

where z is depth.

The negative sign of R_c in (2.2) is necessary to compute positive R_c values as the temporal- and spatial-derivative of c on the left-hand side (LHS) of (2.2) are expected to be negative during the effective filtration stage. Readers are referred to Supplementary B for the analytical solution to (2.2). Intuitively, R_c should depend on the set of parameters in (2.3) which are related to the influent conditions and the filter's initial media characteristics. Readers are referred to Table 2 for the description of these parameters and their anticipated influence on R_c .

$$R_c = f(V_s, L_m, d_p, d_{c,0}, t, \rho_p, \mu_{in}, c_0) \quad (2.3)$$

where V_s is the superficial velocity, L_m the media depth, $d_{c,0}$ the effective grain diameter, ρ_p the bulk density of the turbidity particles suspensions, μ_{in} the fluid dynamic viscosity, and c_0 the influent's concentration value. We note that $c_0(t) = c_0$. By performing dimensional analysis with the Buckingham π -group theorem with the repeating variables of μ_{in} , L_m and t , the following non-dimensional equation can be derived:

$$\pi_1 = f(\pi_2, \pi_3, \pi_4, \pi_5, \pi_6) - (2.4)$$

$$\pi_1 = \frac{R_c L_m^2}{\mu_{in}}, \pi_2 = \frac{c_0 L_m^2}{\mu_{in} t}, \pi_3 = \frac{\rho_p L_m^2}{\mu_{in} t}, \pi_4 = \frac{d_0}{L_m}, \pi_5 = \frac{d_p}{L_m}, \pi_6 = \frac{V_s t}{L_m} - (2.5)$$

The simplest monomial relationship from the functional relationship can then be expressed as:

$$\frac{R_c L_m^2}{\mu_{in}} = C_1 \left(\frac{c_0 L_m^2}{\mu_{in} t} \right)^a \left(\frac{\rho_p L_m^2}{\mu_{in} t} \right)^b \left(\frac{d_0}{L_m} \right)^c \left(\frac{d_p}{L_m} \right)^d \left(\frac{V_s t}{L_m} \right)^e - (2.6)$$

We then use our experimental results (to be discussed later) to determine the most appropriate R_c model equation by imposing a constant 99.5% removal rate of c_0 . We note that the C_1 parameter in (2.6) is assumed to be unity as the first assumption. The usefulness of (2.6) will be discussed in the later section, together with its associated pseudo-algorithm.

3. Workflow of DRFM

We aim to provide flexibility to practitioners to modify the proposed DRFM algorithm, if necessary, to tailor to their industrial operating conditions. Thus, DRFM uses only basic C++ concepts such as dynamic arrays, functions calls, reference pointers and basic data input/output, and avoid the uses of classes and templates (constructors, destructors etc.) which belong to higher level of computer programming.

Referencing to Figure 1, DRFM first requests the user to indicate their choice of filter, i.e. *level1_decisionmaking*, of either single- or dual-media filter. Upon selecting the filter choice, the respective function, i.e. *media_choice1()* for single-media filter or *media_choice2()* for dual-media filter, will be called upon. Within each function, user attends to *level2_decisionmaking* by logging in the values for the filter's initial operating conditions and media characteristics which establish a set of model input parameters. DRFM then undergoes *level1_processrun* whereby each model variable is assigned with a pointer to pointer algorithm to have its own dynamic 2D array size (*[size1][size2]*) for data storage, which depends on the user's choice for $n(\text{size } 1)$

and $t(size\ 2)$ respectively. The use of 2D arrays enables the user to track the development rate of each model variable at any given filter depth (z) and time (t).

By using a nested *for-loop*, DRFM computes the variables (A4 – A11, supplementary), as described in pseudo-algorithm 1, at every computational node which corresponds to a unique z value from the first Δt value until the end of the simulation run. The filter variables at $t = 0$ are initialized with the respective input values by the user. The computations of (A4 – A11, supplementary) under the clogging conditions then begin. At the end of each simulation run, users undergo *level3_decisionmaking* to determine the type of data output to be displayed for any model variable. For convenience, DRFM provides users with 2 options of either *data_plotgraph* or *data_plotscreen* to output the spatiotemporal variation of the selected model variables. The former involves the traditional graphs plotting, whereas the latter prints out the values as a large compact matrix on the console screen for analysis. Finally, we note that DRFM performs the computations sequentially. Parallelism in the computational process is currently not considered.

4. Experiments

To validate the proposed DRFM model, we conducted an experimental study with a single-media pressure filter setup (Figure 2) to strain high-turbid influents under constant-rate rapid filtration mode. The influents were synthesized with PSP polyamide seeding particles (DANTEC, DYNAMICS) suspensions. For the filter setup, the selected sand media was first washed thoroughly with tap water and dried in the oven at 100°C for 24 hours. Mechanical sieving was then carried out after drying to obtain the effective size ($d_{c,0}$) of 0.2mm and uniformity coefficient (UC) of approximately 1.5.

Before each experimental run, appropriate amounts of polyamide particles were added into the influent tank containing 440L of tap water and mixed thoroughly with an inline mixer to obtain the desired turbidity value (Tur_{in}) and average particle size (d_p) for the monodisperse suspension synthesized. Readers are referred to Table 3 for the list of experimental conditions conducted. A minimum d_p value of 20 μ m was

selected for the experiments to simulate the typical particle size range for pre-treatment rapid filtration in seawater desalination as discussed previously. Before the experiments, no additional pre-treatment was adopted for the synthesized suspensions due to the tendency of the polyamide particles to agglomerate easily. Finally, readers are referred to Table 4 for the design parameters relating to the filter setup.

To ensure fully-saturated conditions within the filter, we first backwashed the filter with tap water before commencing on each filtration run. Filtration run was then initiated with tap water only at the maximum pump pressure for 1 minute to check on the consistency of the pressure gauge readings (WIKA digital pressure gauge model DG-10) at Locations 2, 3, 4, 5, 6 and 7 in Figure 2. We note that the average background turbidity for Singapore's tap water is very low at approximately 0.17 NTU (PUB, 2016). The connected valves to the influent and permeate tanks were subsequently fully opened and closed respectively while keeping the magnetic pump switched on. To maintain constant-rate rapid filtration mode, we manually adjusted the flow regulator which recycled a percentage of the influent back to its source tank. The temperature of the influent source was monitored with a glass thermometer which was found to remain constant at 27 - 28°C in all runs. Finally, the readings of the pressure gauge sensors at Locations 2, 3, 4, 5, 6 and 7 were recorded after 5 seconds from the start of the experiment to serve as the clean filter pressure head values.

Pressure head measurements were taken at the above-mentioned locations at regular intervals. At the same time, samples were also extracted from Location 7 for turbidity measurements with a portable Turbidimeter (2100N, HACH Company, USA) and for total suspended solids (*TSS*) measurements. The adopted procedures for turbidity and *TSS* measurements were in accordance to the Standard Methods for the Examination of Water and Wastewater (Standard Methods, 1960). At the end of each filtration run, backwashing of the filter was carried out for 10 minutes to restore the filter back to its original clean state before the next experimental run. We note that we did not employ air scouring for backwashing in our experiments due to resource limitations.

5. Results and discussions

5.1. Validation of DRFM

5.1.1. Predictions of effective filtration stage

With reference to Figures 3a to 3e, all experimental runs (from Table 3) maintained a minimum of 99.5% removal rate of the respective c_0 values, i.e. $\frac{c}{c_0} \leq 0.005$, at the 50cm media depth which indicates that effective filtration stage is attained with the adopted media characteristics. Particle detachment in all runs is minimum at the selected loading rate due to the transient reduction in $\frac{c}{c_0}$ as shown. We note that t' represents the normalized timing which is defined as $\frac{t}{t_{HRT}}$ whereby t is the actual timing and t_{HRT} is the filter's residence time. We also note that the remaining percentage of c_0 (approximately $< 0.5\%$) not removed from the operational filter is likely due to the background concentration of the source water used to synthesize the particle suspensions. By adopting the model input parameters from Table 5, DRFM predicts this physical phenomenon to a good extent (see Figures 4a to 4e). As illustrated in the figures, a very close 100% removal of c_0 is achieved at the normalized media depth ($\frac{z}{L_m}$) of unity, which directly corresponds to $z = 0.5m$, in all simulations runs. We add that Figures 4a to 4e are obtained at the respective final t' value for each simulation run, which will be applied to DRFM's subsequent predictions for the spatial variations of other filter-related parameters.

DRFM also effectively simulates the contrasting effects of the particle size on the spatial variation of $\frac{c}{c_0}$ whereby bulk volumes of bigger particles will be removed within the simulated filter's upper compartments, whereas smaller particles will be removed in a more homogeneous spatial manner as expected. This is evident in Figures 4a to 4c whereby the approximate spatial concentration gradients obtained from the simulated conditions of Experiments 1 to 3 (for $d_p = 50\mu m$) are steeper than that of Experiments 4 and 5 (for $d_p = 20\mu m$) in Figures 4d and 4e for the depth range of $0 \leq \frac{z}{L_m} \leq 0.05$. In summary, the simulation results confirm that DRFM predicts the

spatial clogging inhomogeneity occurring within the simulated filter which is expected in actuality.

5.1.2. Predictions of filter's energy performance

In our analysis, the filter's energy performance is quantified by its energy loss rate occurring due to effective clogging (α') as described in (A11 supplementary). By again using the model input parameters from Table 5, DRFM predicts α' well at $\frac{z}{L_m}$ of unity value as evident by the good agreement obtained in Figures 5a to 5e for the transient comparison between the respective predicted and experimental values for α' . The simulation results indicate that DRFM encapsulates the particle size effect on α' , which quantitative understanding remains limited by far, by adopting the unique length scale definition in (A11 – A12, supplementary) to quantify the surface area effects of the removed particles on α' . We again note that the proposed length scale (θ'_A) is only determined by the respective sizes of the collector grain and turbidity particle which are known a priori. As such, DRFM can predict α' for any given combination of the intake seawater quality conditions and the changing media characteristics within the filter. The predictions will then be useful to optimize the filter's energy performance by altering the controlled operating parameters a priori, and to estimate the optimized timing to backwash the clogged filter for obtaining economies of scale. The manner of which DRFM achieves these objectives will be demonstrated in later sections.

5.1.3. Predictions of variations to filter's properties

Starting with the media's effective size under clogging conditions (d_c), DRFM predicts larger spatial gradients, which corresponds to larger average d_c values, within the filter's upper compartments ($\frac{z}{L_m} \leq 0.1$) during the simulated removal of larger turbidity particles in Figures 6a to 6c (for $d_p = 50\mu m$). This is expected as larger particles have less tendency to penetrate deep into the filter which result in bulk volume of particles to be removed in the uppermost regions as discussed. We

note that DRFM assumes the value of unity for $\frac{d_c}{d_{c,0}}$, which directly corresponds to the original effective size of $d_{c,0}$, at $\frac{z}{L_m} = 0$. In Figures 6d to 6e (for $d_p = 20\mu m$), DRFM instead predicts smaller spatial gradients for d_c in the regions of $\frac{z}{L_m} \leq 0.1$ which implies a more homogeneous spatial distribution of the same mass volume of smaller particles removed within the simulated filter. This is again intuitive as smaller particles have greater tendency to penetrate deeper within the filter. In addition, readers are referred to Figures 7a to 7e which indicate minimum growth rate of d_c (less than 2% of $d_{c,0}$) at $\frac{z}{L_m} = 1$, as compared to that of the upper regions within the filter for all runs, which further underlines the spatial clogging inhomogeneity occurring.

Finally, DRFM predicts greater reduction of the filter's average porosity under clogging conditions (ε_c) in the regions of $\frac{z}{L_m} \leq 0.05$ during the simulated removal of larger particles in Figures 8a to 8c (for $d_p = 50\mu m$). The reduction is, however, less significant in the same region of concern for the simulated removal of smaller particles suspensions in Figures 8d and 8e (for $d_p = 20\mu m$) as expected. Likewise, DRFM assumes the value of ε_0 at $\frac{z}{L_m} = 0$. To further justify the filter's spatial clogging inhomogeneity occurring, the transient reduction of ε_c is also minimum (~2% or less) at $\frac{z}{L_m} = 1$, as compared to the respective ε_c values computed in the upper regions of the simulated filter for all runs, in Figures 9a to 9e.

In summary, DRFM can predict the depth filter's clogging dynamics for a given combination of operating parameters (controlled and non-controlled) by achieving the following.

- Establishing the effective filtration stage for the simulated filter by considering the appropriate particle removal mechanisms
- Demonstrating the inhomogeneous depth removal of turbidity particles occurring within the simulated filter
- Relatively accurate predictions of α' for the simulated filter which is indicative of its energy performance

5.2. Predictions of filter's R_c transient profile

To predict the filter's R_c transient profile for a given combination of operating parameters, we first establish a close representation of (B3, supplementary) in (2.6) by following the hypothesis as described in Table 2. The resulting form of (2.6) is then shown in (5.1) whereby all power coefficients of the π -terms in the original form of (2.6) have been assumed to be unity in our first approach.

$$R_c(z, t) = c_0 \left(\frac{1}{t} \right) \left(\frac{t_{HRT} \rho_p d_p z^2}{t^2 d_{c,0} \mu_{in}} \right)^n - (5.1)$$

We then impose a constant 99.5% removal rate of all Tur_{in} values (c_0) from Table 3 by adopting a best-fit approximate value of -0.002 for the power n parameter in (5.1) with respect to the adopted conditions from Experiments 1 to 5. By using the obtained turbidity values as measured in NTU , the experimental R_c values at the different normalized timings (t') are first computed with (B3, supplementary). Figures 10a to 10e show that the experimental R_c values obtained at $\frac{z}{L_m} = 1$ are near identical to the predicted values from (5.1) with the calibrated n value. As shown in the figures, the transient changes to the R_c values (both experimental and predicted) approach a minimum ($\rightarrow 0$) which suggest that quasi-steady-state is attained. In other words, the effective filtration stage occurred during the experiments whereby the respective R_c values remained sufficiently small for a considerable period.

With respect to (5.1), R_c is directly dependent on the size compatibility between d_p and $d_{c,0}$. Furthermore, $L_m(z)$ and V_s are to be selected carefully to provide sufficient void volumes and contact time for particle removal to be significant, especially during the filtering of higher turbid influents for a considerable period. Finally, ρ_p and μ_{in} are likely not to be too influential on the filter's removal performance as based on our previous experiences for rapid pre-treatment filtration. Operationally, we propose that (5.1) can pre-determine the unique combination of V_s , $d_{c,0}$ and L_m (controlled parameters) which ensures effective rapid filtration by adhering to the following pseudo-algorithm.

Pseudo-algorithm 2

- I. User to input the seawater quality conditions $(c_0, \rho_p, \mu_{in}, d_p)$ for the specific V_s value selected
 - II. User to input total effective filtration period (t_{total}) which corresponds to the t value in (5.1)
 - III. Impose a suitable R_c value on the LHS of (5.1) which corresponds to a minimum 99.5% removal rate of $Tur_{in}(c_0)$ with respect to (B3, supplementary) and the selected t value from step (II)
 - IV. After step (III), there are two unknowns of $d_{c,0}$ and L_m in (5.1)
 - V. Approximate a suitable $d_{c,0}$, via trial and error, with respect to (A7 – A10, supplementary) which ensures 99.5% removal rate of c_0 having the d_p value from step (I)
 - VI. For the selected $d_{c,0}$ value and the known conditions of $c_0, V_s, \rho_p, \mu_{in}, d_p, t$ and R_c , use (5.1) to approximate L_m , via trial and error, by adhering to a suitable empirical value for the power n coefficient which ensures 99.5% removal rate of c_0
-

To ensure longer periods of effective filtration with respect to (5.1), either L_m is increased for a given $d_{c,0}$ value, or $d_{c,0}$ is reduced for a given L_m value while all other variables are kept constant. If materials' constraints are present, then both L_m and $d_{c,0}$ should be appropriately adjusted to balance the increase in the effective filtration time while adhering to the economic budget available. Though sand production is relatively economical, the selected $d_{c,0}$ and L_m values affect the filter's energy performance significantly which in turn determines the filter's backwashing frequency as discussed. In the subsequent sections, we shall demonstrate the hybrid approach of coupling DRFM and the R_c model equation to optimize the filter's energy performance during its effective clogging conditions as illustrated in Figure 11. The proposed pseudo-algorithm for this hybrid model to achieve the optimization objective is as follows.

Pseudo-algorithm 3

- I. User to input the seawater quality conditions ($c_0, \rho_p, \mu_{in}, d_p$) for the specific V_s value
 - II. User to input total effective filtration period (t_{total}) which corresponds to the t value in (5.1) and associated time-step (Δt)
 - III. User to input discretization step (Δz) for L_m to determine number of nodes (n) in the numerical domain for DRFM simulations
 - IV. Impose a suitable R_c value on the LHS of (5.1) which corresponds to a minimum 99.5% removal rate of $Tur_{in}(c_0)$ with respect to (B3, supplementary) and the selected t value from step (II)
 - V. After step (IV), there are two unknowns of $d_{c,0}$ and L_m in (5.1)
 - VI. Approximate a suitable $d_{c,0}$, via trial and error, with respect to (A7 – A10, supplementary) which ensures 99.5% removal rate of c_0 , having the d_p value from step (I), from the start of the filtration operations
 - VII. For the selected $d_{c,0}$ value and the known conditions of $c_0, V_s, \rho_p, \mu_{in}, d_p, t$ and R_c , use (5.1) to approximate L_m , via trial and error, by adhering to a suitable empirical value for the power n coefficient which ensures 99.5% removal rate of c_0
 - VIII. For the given combination of $V_s, d_{c,0}$ and L_m as determined from steps (VI) and (VII), DRFM performs the following computational steps for all nodes at each Δt step till t_{total}
 - a. Compute $D_{c\%}(z, t)$ in (A4, supplementary) by using computed $c(z, t - \Delta t)$ from previous time-step
 - b. Compute $\varepsilon_c(z, t)$ in (A5, supplementary) and $d_c(z, t)$ in (A6, supplementary) by using computed $D_{c\%}(z, t)$ from step (a)
 - c. Compute $\eta_I(z, t)$ in (A7 – a, supplementary) by using $d_c(z, t)$ from step (b), and compute η_G in (A7 – b, supplementary)
 - d. Compute $\eta_c(z, t)$ in (A8, supplementary) as the sum of $\eta_I(z, t)$ and η_G from step (c)
 - e. Compute $\lambda_c(z, t)$ in (A9, supplementary) by using $\varepsilon_c(z, t)$, $d_c(z, t)$ and $\eta_c(z, t)$ from (A5, supplementary), (A6, supplementary) and (A8, supplementary) respectively at the current time-step
 - f. Compute $c(z, t)$ in (A10, supplementary) by using computed $\lambda_c(z, t)$ from step (e)
 - g. Compute $\alpha(z, t)$ and $\alpha'(z, t)$ in (A11, supplementary) under clogging conditions by using computed $\varepsilon_c(z, t)$ and $d_c(z, t)$ from step (b), with the inclusion of θ'_A from (A12, supplementary)
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5.3. Optimizing energy performance of single-media filters

Typically, single-media depth filters are deployed in desalination plants to pre-treat sub-surface intakes having turbidity and TSS values of $< 2 NTU$ and $< 3 mg/L$ respectively (Voutchkov, 2012) under normal operating conditions. The only known large-scale pre-treatment facility which deploys single-media filters is currently

located at Tampa Bay desalination plant in Florida (Tampa Bay), and the only reported operating parameter is the deployment of sand media having $d_{c,0}$ value of 0.7mm. We then adopt the recommended/documented values for the other controlled and non-controlled operating parameters from the references of MWH (2005) and Voutchkov (2012, 2017a) to perform the simulation runs with the hybrid model as described in pseudo-algorithm 3.

Readers are first referred to Table 6 for the model input parameters into pseudo-algorithm 3. Note that the temperature of the simulated filter is assumed to be kept constant at 25 °C and it is expected that it does not vary much among the different pre-treatment facilities. The number of computational nodes for all simulation runs remains as 50. The goal is to determine the unique set of controlled parameters ($d_{c,0}, V_s, L_m$) which optimizes the pre-treatment filter's energy performance during its effective filtration of low- and high-turbid influents having the particle size range of 20 to 100 μ m (Tehowater, 2017) for 48h. We again note that optimizing the filter's energy performance is to best minimize its energy loss rate occurring during effective clogging conditions, which can be identified by the lowest α' value computed at the 48h time mark (α'_{48}) among all varied combinations (Table 6) for $\frac{z}{L_m} = 1$. The average energy cost to pre-treat each unit volume of intake seawater can also serve as an alternative indicator to the filter's energy performance.

We first simulate the larger d_p value of 100 μ m. By adhering to steps (I) to (VII) in pseudo-algorithm 3, we predict five different values of L_m (0.55m, 0.75m, 1.0m, 1.2m, 1.5m) via trial and error, with (5.1) having the empirical value of -0.001 for the n power coefficient which ensures 99.5% removal rate of the given c_0 for 48h. These predicted values of L_m result in significant small R_c values for all simulations runs (Table 6) at the 48h time mark which indicate that effective filtration will occur. To evaluate the filter's energy performance in all simulation runs, we set the maximum allowable α' value to be unity (breakthrough criteria) by equating the filter's maximum energy loss to any designated L_m value. This assumption is reasonable as the maximum energy loss is typically set between 1.8 to 2.4m on the industrial scale (MWH, 2005).

5.3.1. Effects of L_m and V_s on filter's energy performance

With reference to Figure 12a, higher L_m deployed within the simulated filter will gradually reduce α'_{48} when filtering low-turbid influents having the average particle size of $100\mu m$ at fixed V_s values. This is intuitive as the filter's total pore volume increases at larger L_m values which slows down the reduction rate of the filter's initial average porosity. On the contrary, at fixed L_m values, α'_{48} is greater at higher V_s values in Figure 13a when filtering the same influent quality. This is again intuitive as the clogging rate within the filter is faster at higher V_s values (due to higher mass influx) when all other conditions are kept constant during effective clogging conditions.

The varying effects of L_m and V_s on α'_{48} can be best quantified by a best-fit linear approximation (Figures 12a and 13a) for the effective filtration of low-turbid influents comprising of $100\mu m$ turbidity particles. The simulation results have also shown that the first 15 runs from Table 6 have not exceeded the α'_{48} value of unity. This suggests that the current approach of backwashing the operating filters once at every 24 to 48h when filtering low-turbid influents of larger-sized turbidity particles may not provide economies of scale as the filters can still operate for extended periods. To better illustrate the improvements to the filter's energy performance during its effective clogging conditions, we convert the computed α'_{48} values in all runs into α'_p expressed in terms of kilowatt-hour per cubic meter by adhering the following approximation.

$$\alpha'_p = \alpha'_{48} L_m \rho_{sw} g \times 10^{-3} \quad (5.2)$$

where ρ_{sw} is the bulk density of seawater of approximately $1025 kg m^{-3}$, and g the constant gravitational acceleration of $9.81 m s^{-2}$. The computed values for α'_p in all runs are also listed in Table 6. We emphasize that α'_p represents the average additional energy consumption by the filter (due to clogging) to effectively pre-treat every unit m^3 of turbid influents over 48h. The energy consumption due to clean filter conditions is expected to be minimum with the selected initial media characteristics. Ideally, the configuration from run 13 ($L_m = 1.5m, V_s = 5.0m/h$) best optimizes the single-media filter's energy performance when pre-treating low-turbid influents of

100 μm turbidity particles as the computed α'_p is 35% less than the current average of 0.39kwh/m³ in desalination facilities (Voutchkov, 2018).

On the other hand, it is difficult to optimize the filter's energy performance for all combinations during the effective filtration of high turbid influents as the computed α'_p values in all runs exceed 0.39kwh/m³ for all variations of L_m and V_s (see Figures 12b and 13b). An exponential trend can best quantify the effects of varying L_m and V_s on α'_{48} when filtering high-turbid influents comprising of 100 μm turbidity particles. In summary, the simulation results also generally indicate that an increasing L_m value is effective to reduce α'_{48} at higher V_s values, especially for the filtration of low turbid influents. This is an important finding as it underlines that single-media deep filters can achieve optimized energy performance when filtering low-turbid influents of larger-sized particles (Figure 13a) at relatively high loading rate, and can thus operate for extended periods to provide economies of scale.

However, we should also note that an increasing L_m value will gradually violate practicality due to economic constraints. The largest L_m value reported for single-media deep filters by far is 1.8m (MWH, 2005). Thus, the selected value of 1.5m for L_m is economically viable to effectively pre-treat low-turbid influents at 5.0m/h while optimizing energy performance. If budget constraints exist, the selection of other L_m values from Table 6 is still viable for pre-treating low-turbid influents as the final α'_p is still less than 0.39kwh/m³ while ensuring high removal efficacy. Finally, we recognise that there exists a threshold V_s value resulting in significant detachment of the trapped particles within the filter which cannot be handled by DRFM at this moment. This detachment mechanism affects the filter's energy performance and thus remains an important factor to be modelled.

5.3.2. Effects of d_p and $d_{c,0}$ on filter's energy performance

We then adhere to the common set of controlled parameters from run 13 to optimize the filter's energy performance for pre-treating both low- and high-turbid influents of smaller-sized turbidity particles at 5.0m/h. The other conditions of ρ_p , μ_{in} and t_{total} are unchanged. The obtained simulation results from Table 7 indicate that the filter's

removal efficacy ($\eta\%$) reduces to 90.5% and 89.6% when filtering low- and high-turbid influents comprising of $20\mu m$ turbidity particles respectively, and the incurred α'_p values are greater than $0.39kwh/m^3$. Thus, the current value of $0.7mm$ for $d_{c,0}$ must be reduced to maintain the original $\eta\%$ of 99.5% while attempting to optimize the filter's energy performance for handling this influent quality type.

To be most conservative, we first adhere to the proposed R_c model equation in (5.1) to approximate the required $d_{c,0}$ value of $0.15mm$ while maintaining the n power coefficient of -0.001 . However, it is expected that this $d_{c,0}$ value will increase α'_{48} rapidly which hinders the optimization of the filter's energy performance. Thus, we attempt the alternative $d_{c,0}$ values of $0.3mm$ and $0.5mm$ for the same assumed conditions while maintaining the original L_m and V_s values of $1.5m$ and $5.0m/h$ respectively. From Tables 6 and 7, we can confirm that it is very difficult to improve the energy performance of single-media depth filters when filtering high-turbid influents (20 to $100\mu m$ turbidity particles) with the latter two $d_{c,0}$ values as the computed α'_{48} values cannot be kept below unity. Likewise, the respective α'_p computed are higher than the average value of $0.39 Kwh/m^3$ which is undesirable. The simulation results also indicate that the single-media depth filters are not likely to optimize their energy performance when pre-treating low-turbid influents of $20\mu m$ turbidity particles. The best option to achieve economies of scale with single-media depth filters is to use $1.5m$ depth of $0.5mm$ $d_{c,0}$ value to pre-treat low-turbid influents having $100\mu m$ turbidity particles at $5.0m/h$.

In summary, the above-discussed hybrid approach (pseudo-algorithm 3) can subsequently be applied by practitioners to optimize the energy performance of single-media filters for any given set of low-turbid influent conditions. We also add that each simulation run requires minimum computational resources. Hence, with the current developments of artificial intelligence (AI), the hybrid approach enables practitioners to perform data-driven modelling for pre-determining the single-media depth filter configuration, particularly for new desalination plants, which optimizes their energy performance for a wide combinations of operating parameters.

5.4. Optimizing energy performance of dual-media filters

Extending the proposed hybrid approach to dual-media depth filters is desirable as the dual-media configuration remains common in large-scale desalination plants today (Carlsbad, 2016; Water Technology, 2016). As our first approach, we regard the effluent concentration from the top media depth as the influent concentration into the tip of the bottom media depth at each time step, and perform the standardised computations from pseudo-algorithm 3 for each media layer having their own ε_0 value. For DRFM, this can be done by adding additional algorithm lines between the sequential computations of the respective top and bottom media layers which directly equate the effluent concentration from the top media depth, at the end of the current time step, as the influent concentration into the bottom media depth at the same time step.

We again perform 30 sets of simulation runs by using the recommended $d_{c,0}$ values of 1mm and 0.6mm for the anthracite and fine sand respectively (Voutchkov, 2012, 2017a) while maintaining a dual-media depth of 1.8m and keeping the simulated temperature constant at 25 °C. Via trial and error method with the R_c model equation in pseudo-algorithm 3, we approximate varying values of L_m (Table 8) for both anthracite and sand to pre-treat both low- and high-turbid influents having the particle size range of 20 to 100 μ m for 48h. The objective is again to pre-determine the unique set of controlled parameters which best optimizes the dual-media filter's energy performance for the regarded influent conditions.

5.4.1. Effects of L_m and V_s on filter's energy performance

We first note that the computed α'_{48} values for the bottom sand media layer remain minimum ($\sim 10^{-6}$) in all simulation runs from Table 8 as the bulk volume of 100 μ m turbidity particles are removed within the upper anthracite layer which is expected. Hence, the energy performance of the sand layer is well-optimized over 48h, and the analysis thus focuses on the upper anthracite media layer. Likewise, an increasing L_m value for the anthracite layer gradually reduces α'_{48} at fixed V_s values (Figures 14a and 14b) when filtering low- and high-turbid influents comprising of 100 μ m turbidity particles, which thus improves the energy performance within the anthracite layer. Contrary to the single-media analysis, the effects of varying L_m on α'_{48} for dual-

media configurations can be best quantified by an exponential trend, as shown in the figures, when filtering both types of influent conditions. For increasing V_s values at fixed L_m values, similar conclusion about α'_{48} from the previous single-media analysis can also be made for the dual-media filtration of the same influent quality (Figures 15a and 15b). The only difference is that a best-fit linear fit trend can best quantify the effect of varying V_s on α'_{48} for dual-media filtration.

Importantly, the simulation results from Table 8 also indicate that dual-media filters are likely to operate for extended periods when filtering low-turbid influents of large turbidity particles as the computed α'_{48} values within the anthracite layer have not attained unity, which is indicative of its optimized energy performance. Furthermore, the computed α'_p values for runs 1 to 15 in the same table are less than $0.39 \text{ Kwh}/\text{m}^3$. However, it is still difficult for dual-media filters to optimize their energy performance when pre-treating high turbid influents in runs 16 to 30. From the obtained simulation results, the dual-media configuration from run 15 best optimizes its energy performance when filtering low-turbid influents of $100\mu\text{m}$ particles at high production rate.

5.4.2. Effects of d_p and $d_{c,0}$ on filter's energy performance

To effectively filter $20\mu\text{m}$ turbidity particles, we concurrently reduce the current sizes of anthracite and sand from run 15, while maintaining size compatibility ratio between both media types (Table 9). Unexpectedly, it is again difficult to optimize the filter's energy performance when filtering both low- and high-turbid $20\mu\text{m}$ particles suspensions as the computed α'_p for runs A to E in Table 9 are greater than $0.39 \text{ Kwh}/\text{m}^3$. Generally, dual-media filters may be preferred to single-media filters to pre-treat low-turbid influents having larger-sized turbidity particles as they achieve better energy performance at higher production rate, with respect to the compared α'_p values in runs 1 to 15 between Table 6 and 8. On the contrary, it still remains a research challenge to optimize the filter's energy performance for both single- and dual-media configurations when pre-treating high-turbid influents of smaller-sized turbidity particles.

Comparing the obtained simulation results from Tables 6 and 8 also interestingly suggest that single-media depth filters may be a better option to indefinitely pre-treat low-turbid influents of large sized turbidity particles, notwithstanding its slightly inferior energy performance, i.e. higher α'_{48} or α'_p values incurred at higher loading rates when all other variables are kept constant. This is because the bottom sand layer in the dual-media configuration is currently not involved in the pre-treatment process. Hence, its long-term capital investment may not be necessary, particularly for situations whereby the intake seawater quality is usually or always good. On the other hand, it can also be debated that the bottom sand layer serves to remove the detached particles from the upper coarse layer during operations (cannot be predicted by DRFM at this moment), or to serve as an additional filter layer for extreme high turbid influents in rare scenarios.

In summary, the careful selection between single- and dual-media configuration to best optimize the filter's energy performance requires detailed investigations of the following factors: (a) range of particle concentrations from the intake location, (b) range of particle sizes in the influent source, (c) types of pre-treatment chemicals involved, (d) frequency of high-turbid influents' intakes, (e) maximum allowable α' for the operating filter, (f) availability of capital funds, and etc. The multitude of factors to be considered reflects the complexity in decision-making, which can be alleviated by performing data-driven modelling for a large combinations of operating parameters with the proposed DRFM hybrid model in pseudo-algorithm 3.

5.5. Predicting exceedance in filter's energy performance

DRFM's predictions of α' (Figures 5a to 5e) indicates that the proposed algorithm can predict the time of exceedance in the filter's energy performance, i.e. breakthrough stage, with the known operating conditions. Every pre-treatment filter facility acquires a unique breakthrough energy loss rate value (α'_b) which is then set as the breakthrough criteria. With the known operating conditions of $d_{c,0}$, V_s , c_0 , ε_0 and L_m , we modify the original forms of (A11, supplementary) and (A4, supplementary) to obtain (5.3a) and (5.3b) respectively.

$$\alpha'_b = \theta'_A \left[150 \frac{V_s v (1 - \varepsilon_0 + D_{c\%,b}(z, t_b))^2}{g(d_{c,0}(1 + D_{c\%}(z, t_b)))^2 (\varepsilon_0 - D_{c\%,b}(z, t_b))^3} + 1.75 \frac{V_s^2 (1 - \varepsilon_0 + D_{c\%,b}(z, t_b))}{g(d_{c,0}(1 + D_{c\%}(z, t_b))) (\varepsilon_0 - D_{c\%,b}(z, t_b))^3} \right] - \theta'_A \alpha(z, 0) \quad (5.3a)$$

$$t_b = \left(\frac{\rho_p L_m(z) \varepsilon_0 D_{c\%,b}(z, t_b)}{c_0 V_s} \right) - (5.3b)$$

where $D_{c\%,b}$ is the breakthrough clogging degree, and t_b the filter's approximate breakthrough time. An iterative algorithm (see pseudo-algorithm 4) can subsequently be developed to represent (5.3) which enables practitioners to approximate t_b a priori at any given filter depth and estimate the optimized timing for filters' maintenance to obtain economies of scale.

Pseudo-algorithm 4

- I. User to input the known operating parameters ($c_0, \rho_p, \mu_{in}, d_p, V_s, L_m, \varepsilon_0, d_{c,0}$)
 - II. User to input the step size for the filter's clogging degree ($\Delta D_{c\%}$)
 - III. Maximum filter's clogging degree ($D_{c\%,max}$) is set as 100%
 - IV. For first $\Delta D_{c\%}$ till $D_{c\%,max}$, perform the following computations.
 - a. Compute α' by using the known conditions of ($c_0, \rho_p, \mu_{in}, d_p, V_s, L_m, \varepsilon_0, d_{c,0}$)
 - b. If $\alpha' \geq \alpha'_b$, compute t_b from (5.3b) by using known conditions of ($c_0, \rho_p, \mu_{in}, d_p, V_s, L_m, \varepsilon_0, d_{c,0}$) and specific $D_{c\%}$ value, else return back to step (a) and continue computations
-

To ensure that pseudo-algorithm 4 works to approximate t_b for any given combination of the operating parameters, we underline that $\Delta D_{c\%}$ must be sufficiently small to minimize the errors incurred during the iterative process. By adopting the value of 10^{-4} for $\Delta D_{c\%}$, we approximate the respective t_b values for the single-media filtration simulations runs (Tables 6 and 7) while adhering to the α'_b value of unity. For dual-media filtration, we assume that the breakthrough occurs in the upper coarse anthracite layer first before the sand layer. By doing so, we again approximate the respective t_b values as listed in Tables 8 and 9 for the anthracite

layer while still adopting α'_b value of unity. We, however, emphasize that this iterative approach is only an approximation and should continue be improved on to achieve better accuracy.

5.6. Economies of scale analysis

In this section, we demonstrate the economies of scale benefit provided by the filter's optimized energy performance on the total energy cost (TEC) incurred by desalination facilities in general. We first summarize the relevant costs associated with the pre-treatment step in Figure 12 and define TEC in (5.4) for a given volume of intake seawater (V_1) and produced volume of backwash waste (V_2) during filters' maintenance. Generally, the entirety of the pre-treatment step (operational and maintenance phases) consumes a minimum of $0.60 \text{ Kwh}/\text{m}^3$ (Zarzo and Prats, 2018).

$$\text{Total energy cost (TEC)} = EC_1 + EC_2 + EC_3 + EC_4 \quad (5.4)$$

EC_1 – Energy cost associated with the effective pre-treatment filtration ($\alpha'_p \times V_1 \times \$0.12 \text{ USD}/\text{Kwh}$)

EC_2 – Chemical cost associated with treatment of produced backwash waste ($0.05 \text{ USD}/\text{m}^3 \times V_2$)

EC_3 – Energy cost associated with management of treated backwash waste ($0.27 \text{ Kwh}/\text{m}^3 \times V_2 \times \$0.12 \text{ USD}/\text{Kwh}$)

EC_4 – Energy cost associated with RO treatment step ($0.79 \text{ Kwh}/\text{m}^3 \times V_1 \times \$0.12 \text{ USD}/\text{Kwh}$)

By assuming an intake rate of $Q \text{ m}^3/\text{d}$, we note that $V_1 = Q \times \frac{t_{total}}{24h}$ whereby t_{total} is taken as the predicted t_b value from Runs 1 to 15 (Tables 6 and 8) when pre-treating low-turbid influents of $100\mu\text{m}$ turbidity particles, and $V_2 = 0.04V_1$ which assumes an average backwash waste volume of 4% of the total intake volume (Voutchkov, 2012 and 2017a). We only focus on the low-turbid influents of $100\mu\text{m}$ turbidity particles as the smaller-sized turbidity particles suspensions remain difficult to manage as demonstrated previously. We then compute the total energy cost for each unit

volume of desalinated water (β) for each of the associated simulation runs in the following.

$$\beta = \frac{TEC}{V_1} \quad (5.5)$$

We also compute the respective β values from t_{total} of 48h while keeping the other model input values unchanged. The other assumptions for performing the cost analysis are as follows.

- 100% recovery rate from the operating pre-treatment rapid filters (both single- and dual-media)
- All operating filters are gravity-driven thus EC_1 only refers to the pumping costs for maintaining constant-rate rapid filtration during effective clogging conditions
- Energy cost due to clean filter conditions is expected to be minimum as compared to the incurred energy cost due to effective clogging conditions
- For simulation runs adopting the predicted t_b under normal operating conditions, there will only be 1 backwash cycle carried out at timing t_b
- For simulation runs adopting the 48h operational period under the same operating conditions, there will be m backwash cycles carried out whereby $m = \text{int} \left(\frac{t_b}{48h} \right)$ and $\text{int} ()$ is an integer function.
- Each backwash cycle produces the same volume of backwash waste for further treatment and disposal
- The electricity cost of \$0.12 USD/Kwh is the current average in the United States (Ovo Energy, 2018) and this cost varies among the different nations. In Singapore, the current cost is around \$0.214 SGD/Kwh.
- Chemical cost of \$0.05 USD/m³ is assumed to include the indirect energy for producing the required chemicals

By keeping all other conditions constant, the simulations run which adopt the 48h operational period will result in higher β due to greater number of backwash cycles carried out as compared to the respective run which adopt the predicted t_b operational period. We then introduce a unique indicator in (5.6) to demonstrate the economies of scale benefit for each of the associated simulation runs.

$$\gamma = \frac{\beta_{48h}}{\beta_{t_b}} \quad (5.6)$$

where γ is the ratio between β_{48h} incurred at 48h and β_{t_b} incurred at t_b timing. Higher γ values, computed for larger t_b values, indicate larger energy cost savings due to the extended production rate from the operating filters before maintenance (backwashing phase) and vice versa. Readers are referred to Table 10 which lists the respective γ value computed from (5.6) for each of the simulation run stated.

As expected, those runs associated with lower hydraulic loading rates generally result in higher energy cost savings, i.e. higher γ values, as the clogging rate of these operating filters is generally lower for the assumed influent conditions. However, for these filters to meet the required intake rate of $Q \text{ m}^3/d$, additional filters are required to be built which result in higher capital costs as compared to filters operating at higher hydraulic loading rates. Hence, proper decision-making is needed to achieve an optimal balance between the capital costs and *TEC* in the long run. Table 10 also indicates the preference of dual-media filters' deployment as these filters can generally operate for longer periods, as compared to single-media depth filters for the same assumed conditions, due to their larger clogging capacity which then result in larger savings in *TEC*. In summary, optimizing the filter's energy performance during effective clogging conditions with the DRFM hybrid model is useful to provide economies of scale indefinitely, especially when pre-treating low-turbid influents of larger-sized turbidity particles. As demonstrated, we can achieve a prolonged reduction in the specific energy cost associated with managing the backwash waste during maintenance due to the economies of scale benefit. This subsequently reduces the total energy cost of each unit volume of desalinated water for an increasing urban population which is an important objective as discussed. On the contrary, the proper management of high-turbid influents, especially for smaller-sized turbidity particles, to maintain an optimal balance between effective filtration and optimized filter's energy performance remains an important research problem.

5.7. Model limitations

A few limitations in DRFM must be underlined. Firstly, the current DRFM version cannot function for the filtration of natural organic matters (NOMs) which are typically less than $0.45\mu\text{m}$ and cannot be effectively removed from the influent source via straining and the other particle removal mechanisms from Table 1. To address to this issue, the DRFM algorithm must consider the physical adsorption of NOMs into the pores of the collector grains, or the more complicated biofilm absorption of NOMs on the surface of the grain itself. For the latter, a concentration gradient is usually involved within a thin film around the collector grain which is expected to grow over time especially for deep biofilms. Concurrently, a unique relationship between the removal of NOMs and the proliferation of marine bacteria colonies within the thin film must be introduced to approximate the transient growth of the collector grain, which affects the filter's energy loss rate as demonstrated in this study.

DRFM is currently based on the assumption that particle detachment is negligible which may not be representative of actuality, particularly for filtration cases having high hydraulic loading rates or large temporal variability in the intake source. Besides the energy loss rate criteria, breakthrough can also be attained by the rapid rise in the effluent concentration which cannot be effectively handled by DRFM at this moment due to the assumed absence of the detachment coefficient in (A1). Though the transient growth of the collector grain results in a gradual reduction of the filter's effective removal efficacy over time in both (A7) and (A8), the slow transient rise in the effluent concentration from the simulation results is unlikely to match with that of actuality. However, it is also worth noting that the detachment mechanism remains difficult to quantify due to its dependence on a multitude of filter's operating parameters.

For the filtering of very large particles (significant straining effect), effective contaminant removal will still occur, however, on the account of surface layer clogging as the particles are likely to accumulate on the tip of the top media surface. Consequently, the energy loss rate (A11) computed will not be entirely accurate as minimum changes to the dimensions of the collector grains (in actuality) are expected during surface layer clogging. This problem could be addressed by introducing an additional scalar parameter in DRFM which computes the transient growth of a thin particle layer on the tip of the top media surface, while assuming minimum changes to the original dimensions of the collector grains

Finally, DRFM only functions effectively for influent source having low polydispersity which is usually achieved with proper pre-treatment (coagulation and flocculation steps) prior to the filtration step. Influent having high polydispersity could render DRFM's predictive capability ineffective as there is currently no precise method to quantify the different particle sizes with a singular model input parameter. This remains an open research problem.

5.8. Model extensions

5.8.1. Extension to biofiltration modelling

Sub-surface intake systems are expected to garner increasing attention as these systems minimize energy costs and environmental impacts (Missimer et al., 2013; Dehwah and Missimer, 2016). To extend DRFM to these systems, modelling the biofiltration mechanism becomes the focus. As part of our current works, we shall describe the notable differences from the current version of DRFM. Firstly, depth removal of NOMs still exists, however, over a longer time scale (diffusion time scale) due to an order reduction in the hydraulic loading rate for biofiltration. Secondly, the collector grain will still gradually grow over time, however at a much slower rate, as a thin biofilm layer develops around its surface to conserve the volume mass of NOMs removed within the filter. A unique relationship between the synthesis of the marine bacteria colonies and the volume mass of NOMs removed is then required over the defined time scale. The first possible approach is to adhere to the empirical Monod equation (Rittmann and McCarthy, 2001) to approximate the synthesis rate of the bacteria colonies within the thin film for a given spatial concentration of NOMs removed within the filter. Based on previous works, the thin biofilm layer typically requires about 4 to 6 weeks to develop (Voutchkov, 2012, 2017a). An appropriate relationship between the synthesis rate and the growth rate of the collector grain must also be assumed which directly affect the filter's global voidage over time. The energy loss rate is then subsequently computed from the changing effects of the filter's properties as demonstrated in this study. Likewise, the objective of the revised model is to predict the optimized timing to backwash the biofilter system which is expected to take place after longer periods of operations as compared to rapid filter systems. This is an important consideration as maintenance of sub-surface intake

systems is difficult and energy-intensive. Finally, we note that the revised model to attend to the biofiltration mechanism will be termed as Dynamical Slow Filtration Model (DSFM).

6. Closing remarks

In summary, a Dynamical Rapid Filtration Model (DRFM) hybrid model has been developed in this study to pre-determine the filters' configurations (both single- and dual-media) which optimize their energy performance, i.e. lowering the current industrial average value of $0.39kwh/m^3$, during the effective pre-treatment of low-turbid influents comprising of larger-sized turbidity particles. By doing so, we can subsequently predict the optimized timing to backwash the clogged filters as based on the energy loss rate criterion for achieving economies of scale indefinitely. The DRFM hybrid model comprises of DRFM itself and an empirical contaminant mass removal (R_c) model equation to address to the hybrid relationship between effective filtration and the filter's energy loss rate occurring. Validations of both unique models have been achieved by the good agreement obtained between our experimentally derived results and respective predicted values.

We then demonstrate on how the DRFM hybrid model can optimize the filter's energy performance for any set of operating parameters (controlled and uncontrolled) by introducing quantitative indicators to illustrate the optimization effect. The obtained simulation runs suggest the possible impracticality of backwashing the filters at fixed intervals of 24 to 48h when pre-treating low-turbid influents of larger-sized turbidity particles as the filters can still operate for an extended run to provide the economies of scale benefit. On the contrary, high-turbid influents remains a hindrance to manage due to the difficulty in maintaining a balance between effective filtration and the filter's energy loss rate occurring. Finally, we have introduced a unique indicator to demonstrate the economies of scale benefit on a broader sense by reducing the energy cost associated with managing the backwash waste during maintenance. This concurrently reduces the total energy cost for each unit volume of desalinated water.

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Nomenclature

c	Concentration scalar
c_0	Initial concentration of turbidity particles suspension
$D_{c\%}$	Clogging degree percentage
$D_{c\%,max}$	Maximum clogging degree percentage of filter
$d_{c,0}$	Effective size of grain under clean filter conditions
d_c	Effective size of grain under clogging filter conditions
d_p	Average diameter of particle
EC_1	Energy cost associated with the pre-treatment filtration of intake seawater volume
EC_2	Chemical cost associated with treatment of produced backwash waste
EC_3	Energy cost associated with management of treated backwash waste
EC_4	Energy cost associated with RO treatment step
F	Theoretical filter capacity
g	Gravitational acceleration
$\hat{G}$	Total molar generation rate per unit volume
$h(t)$	Scalar height of thin layer formation during surface layer clogging
J	Hydraulic gradient
k_1	Attachment coefficient
k_2	Detachment coefficient
L_m	Media depth
m	Number of backwash cycles for filters adopting the 48h operational period
n	Number of computational nodes
q_{in}	Inlet hydraulic loading rate
Q	Assumed seawater intake rate
R_c	Total mass removal rate of the contaminants per unit volume of fluid
TEC	Total energy cost incurred by SWRO facilities
Tur_{in}	Influent turbidity value
TSS	Total suspended solids concentration
t_{HRT}	Hydraulic retention time of experimental filter
t	Time
t_b	Filter's breakthrough timing
t'	Normalized timing
t_{total}	Total effective filtration period
v	Velocity
V_s	Superficial velocity
V_1	Volume of intake seawater
V_2	Volume of backwash waste
UC	Uniformity coefficient
$\vec{u}$	Molar-averaged velocity vector
y	Downward displacement parameter
z	Filter depth

Symbols

σ	Specific deposit
λ_c	Filter coefficient under clogging conditions
ρ_p	Bulk density of turbidity particles suspensions
ν	Fluid kinematic viscosity
μ_{in}	Fluid dynamic viscosity
η_c	Effective filtration efficacy
η_I	Interception efficacy
η_G	Gravitational sedimentation efficacy
ε_0	Filter's clean average porosity
ε_c	Filter's clogging average porosity
α	Filter's total energy loss rate (dimensionless)
α'	Filter's energy loss rate due to clogging (dimensionless)
α'_b	Filter's breakthrough energy loss rate (dimensionless)
α'_{48}	Filter's energy loss incurred at the 48h time mark (dimensionless)
α'_p	Energy cost to pre-treat per cubic metre of intake seawater
θ'_A	Length scale
β	Total energy cost for each unit volume of desalinated water
γ	Indicator for economies of scale analysis

List of Figures

- FIGURE 1. Simplified illustration of workflow in DRFM to compute filter-related parameters ($c, D_{c\%}, d_c, \varepsilon_c, \alpha, \eta, \lambda$) during effective filtration stage.
- FIGURE 2. Simplified schematic representation of single-media rapid pressure filter setup
- FIGURE 3. Transient variations of normalized discharge concentration ($\frac{c}{c_0}$) at 50cm media depth of lab-scale rapid filter setup: (a) Exp 1, (b) Exp 2, (c) Exp 3, (d) Exp 4, and (e) Exp 5.
- FIGURE 4. DRFM predictions for simulated filter's spatial variations of discharge concentration ($\frac{c}{c_0}$) at final t' values for experimental conditions from Table 3: (a) Exp 1, (b) Exp 2, (c) Exp 3, (d) Exp 4, and (e) Exp 5.
- FIGURE 5. DRFM predictions for energy loss rate due to clogging (α') at normalized media depth ($\frac{z}{L_m}$) of unity for experimental conditions from Table 3: (a) Exp 1, (b) Exp 2, (c) Exp 3, (d) Exp 4, and (e) Exp 5.
- FIGURE 6. DRFM predictions of simulated filter's spatial variations of media's normalized effective size ($\frac{d_c}{d_{c,0}}$) at final t' values for experimental conditions from Table 3: (a) Exp 1, (b) Exp 2, (c) Exp 3, (d) Exp 4, and (e) Exp 5.
- FIGURE 7. DRFM predictions of transient variations of media's normalized effective size ($\frac{d_c}{d_{c,0}}$) at normalized media depth ($\frac{z}{L_m}$) of unity for experimental conditions from Table 3: (a) Exp 1, (b) Exp 2, (c) Exp 3, (d) Exp 4, and (e) Exp 5.
- FIGURE 8. DRFM predictions of spatial variations of filter's average porosity (ε_c) at final t' values for experimental conditions from Table 3: (a) Exp 1, (b) Exp 2, (c) Exp 3, (d) Exp 4, and (e) Exp 5.
- FIGURE 9. DRFM predictions of transient variations of filter's average porosity (ε_c) at normalized media depth ($\frac{z}{L_m}$) of unity for experimental conditions from

Table 3: (a) Exp 1, (b) Exp 2, (c) Exp 3, (d) Exp 4, and (e) Exp 5.

FIGURE 10. Comparison between experimental and predicted R_c values from (5.1): (a) Exp 1, (b) Exp 2, (c) Exp 3, (d) Exp 4, and (e) Exp 5.

FIGURE 11. Simplified illustration of hybrid approach involving DRFM and R_c model equation to optimize rapid filtration operations. For simplicity, we only confined the illustration to 9 combinations of L_m and $d_{c,0}$ for an infinite combination of influent conditions which is to be operated for an effective filtration period of t_{total} .

FIGURE 12. Effects of varying sand media depth (L_m) on the filter's energy loss rate incurred at the 48h time mark (α'_{48}) at fixed hydraulic loading rates (V_s): (a) effective filtration of low-turbid influents of 100 μm turbidity particles, and (b) effective filtration of high-turbid influents of 100 μm turbidity particles

FIGURE 13. Effects of varying hydraulic loading rates (V_s) on the filter's energy loss rate incurred at the 48h time mark (α'_{48}) at fixed sand media depth (L_m): (a) effective filtration of low-turbid influents of 100 μm turbidity particles, and (b) effective filtration of high-turbid influents of 100 μm turbidity particles

FIGURE 14. Effects of varying anthracite media depth (L_m) on the filter's energy loss rate incurred at the 48h time mark (α'_{48}) at fixed hydraulic loading rates (V_s): (a) effective filtration of low-turbid influents of 100 μm turbidity particles, and (b) effective filtration of high-turbid influents of 100 μm turbidity particles

FIGURE 15. Effects of varying hydraulic loading rates (V_s) on the filter's energy loss rate incurred at the 48h time mark (α'_{48}) at fixed anthracite media depth (L_m): (a) effective filtration of low-turbid influents of 100 μm turbidity particles, and (b) effective filtration of high-turbid influents of 100 μm turbidity particles

FIGURE 16. Summary of energy costs associated with pre-treatment step in SWRO facilities

List of Tables

- TABLE 1. Description of physical mechanisms to remove turbidity particles within a granular filter
- TABLE 2. Anticipated effects of influent and media characteristics parameters on filter's removal performance with respect to R_c
- TABLE 3. Experimental operating conditions
- TABLE 4. Design parameters of single-media rapid pressure filter setup
- TABLE 5. Model input parameters into DRFM for the experimental conditions from TABLE 3
- TABLE 6. Model input parameters into pseudo-algorithm 3 (DRFM hybrid approach) to optimize single-media depth filtration, with simulation results provided (last 4 columns)
- TABLE 7. Simulation runs for single-media filtration of 20 μ m turbidity particles with modifications to $d_{c,0}$ values from runs 13 and 28 in Table 6
- TABLE 8. Model input parameters into pseudo-algorithm 3 (DRFM hybrid approach) to optimize dual-media depth filtration, with simulation results provided (last 3 columns)
- TABLE 9. Simulation runs for dual-media filtration of 20 μ m turbidity particles with modifications to $d_{c,0}$ values from runs 15 and 30 in Table 8
- TABLE 10. Analysis of economies of scale benefit on total energy cost (TEC) incurred by SWRO facilities

List of Figures

FIGURE 1.

FIGURE 2.

FIGURE 3.

FIGURE 4.

FIGURE 5.

FIGURE 6.

FIGURE 7.

FIGURE 8.

FIGURE 9.

FIGURE 10.

FIGURE 11.

FIGURE 12.

FIGURE 13.

FIGURE 14.

FIGURE 15.

FIGURE 16.

List of Tables

TABLE 1.

Mechanism	Description	References
Interception	Particle deposition occurs when any turbidity particle comes within a particle's radius from the surface of singular grain	Yao et al. (1971); Rajagopalan and Tien (1976); Tien (1989)
Inertial impaction	Particle deposition occurs when any turbidity particle, due to its mass inertia, deviates from its corresponding streamlines and intersect with surface of singular grain	George and Poehlein (1976); Tien (1989)
Brownian diffusion	Particle deposition is significant for turbidity particle of sub-micron size due to the Brownian diffusion force acting on it and causing it to intersect with surface of singular grain	Yao et al. (1971); Tien (1989)
Gravitational sedimentation	Particle deposition occurs when any turbidity particle moves away from corresponding streamlines, due to gravitational force, and intersect with surface of singular grain	Yao et al. (1971); Tien (1989)
Electrostatic forces	Grain may carry electrostatic charges and act an electrostatic force on incoming turbidity particle, causing it to intersect with grain's surface. Particularly important for fluidized granular beds	Tien (1989)
Straining	Removal of turbidity particle occurs when the average size of the particle is bigger than the average pore-size of the filter	Tien (1989), MWH (2005)

TABLE 2

Parameter	Definition	Significance
Superficial velocity (V_s)	Hydraulic loading rate	Smaller $V_s \rightarrow$ greater R_c
Media depth (L_m)	Depth of either fine sand or coarse media layer	Greater $L_m \rightarrow$ greater R_c
Particle size (d_p)	Average size of turbidity particles	Greater $d_p \rightarrow$ greater R_c
Media size ($d_{c,0}$)	Effective size of either fine sand or coarse media layer	Smaller $d_{c,0} \rightarrow$ greater R_c
Influent concentration (c_0)	Taken as either initial total suspended solids (TSS) or initial turbidity of influents	Greater $C_0 \rightarrow$ greater R_c
Dynamic viscosity (μ_{in})	Viscosity of influents	Smaller $\mu_{in} \rightarrow$ greater R_c
Density of particles (ρ_p)	Bulk density of turbidity particles	Greater $\rho_p \rightarrow$ greater R_c

TABLE 3

Exp no.	q_{in} (m/h)	$Tur_{in}(c_0)$ (NTU)	$TSS(c_0)$ (mg/L)	d_p (μm)	Duration ($mins$)
1	6.0	78.8	158	50	90
2	6.0	68.0	140	50	120
3	6.0	86.1	170	50	120
4	6.0	75.6	151	20	90
5	6.0	63.6	127	20	90

TABLE 4

Parameter	Value
Inner diameter of column (m)	0.15
Height of column (m)	1.25
Volume of influent and permeate tanks (m^3)	0.44

TABLE 5

Parameter	Value
Media depth, L_m (m)	0.5
Media effective size, $d_{c,0}$ (mm)	0.20
Influent hydraulic loading, V_s (m/h)	6.0
Polyamide particle sizes, d_p (μm)	20, 50
Polyamide particles bulk density, ρ_p (kg/m^3)	1030
Influent TSS , c_0 (mg/L)	100 - 200
Clean bed porosity, ε_0 (dimensionless)	0.35 ~ 0.4
Fluid's dynamic viscosity, μ_{in} (kg/ms)	0.84×10^{-3}
Fluid's kinematic viscosity, ν (m^2/s)	0.84×10^{-6}
Experimental duration, t_{total} (s)	5400, 7200
Number of computational nodes, n	50

TABLE 6

Run	c_0^{**} (kg/m ³)	V_s^* (m/h)	L_m^{***} (m)	R_c at 48h (s ⁻¹)	α'_{48}	α'_p at 48h (kwh/m ³)	ε_c at 48h	t_b (h)
1	0.004	5.0	0.55	0.0000117	0.0685	0.379	0.396	624
2	0.004	7.5	0.55	0.0000117	0.157	0.868	0.394	300
3	0.004	10.0	0.55	0.0000117	0.285	1.58	0.392	179
4	0.004	5.0	0.75	0.0000116	0.0510	0.385	0.397	850
5	0.004	7.5	0.75	0.0000116	0.131	0.988	0.395	410
6	0.004	10.0	0.75	0.0000116	0.211	1.59	0.394	244
7	0.004	5.0	1.0	0.0000116	0.0338	0.340	0.398	1130
8	0.004	7.5	1.0	0.0000116	0.0771	0.775	0.397	546
9	0.004	10.0	1.0	0.0000116	0.175	1.76	0.395	326
10	0.004	5.0	1.2	0.0000116	0.0224	0.270	0.398	1360
11	0.004	7.5	1.2	0.0000116	0.0641	0.773	0.397	655
12	0.004	10.0	1.2	0.0000116	0.139	1.68	0.396	390
13	0.004	5.0	1.5	0.0000116	0.0168	0.253	0.399	1710
14	0.004	7.5	1.5	0.0000116	0.0511	0.771	0.398	819
15	0.004	10.0	1.5	0.0000116	0.104	1.57	0.397	488
16	0.100	5.0	0.55	0.000291	3.69 (> 1)	20.4	0.296	25.0
17	0.100	7.5	0.55	0.000292	13.9 (> 1)	76.9	0.244	12.0
18	0.100	10.0	0.55	0.000292	48.0 (> 1)	265	0.192	7.16
19	0.100	5.0	0.75	0.000291	2.14 (> 1)	16.1	0.324	34.0
20	0.100	7.5	0.75	0.000291	6.69 (> 1)	50.5	0.286	16.4
21	0.100	10.0	0.75	0.000291	17.5 (> 1)	132	0.248	9.78
22	0.100	5.0	1.0	0.000290	1.40 (> 1)	14.1	0.343	45.4
23	0.100	7.5	1.0	0.000291	3.96 (> 1)	39.8	0.314	21.8
24	0.100	10.0	1.0	0.000291	8.98 (> 1)	90.3	0.286	13.2
25	0.100	5.0	1.2	0.000290	1.10 (> 1)	13.3	0.352	54.0
26	0.100	7.5	1.2	0.000290	2.91 (> 1)	35.1	0.329	26.2
27	0.100	10.0	1.2	0.000291	6.33 (> 1)	76.4	0.305	15.6
28	0.100	5.0	1.5	0.000290	0.810	12.2	0.362	68.0
29	0.100	7.5	1.5	0.000290	2.10 (> 1)	31.7	0.343	32.8
30	0.100	10.0	1.5	0.000290	4.34 (> 1)	65.5	0.324	19.5

$d_p = 100\mu m^*$, $\rho_p = 1050 kg/m^3^*$, $\mu_{in} = 0.89 \times 10^{-3} kg/ms^*$, $d_{c,0} = 0.7mm^*$, $\varepsilon_0 = \sim 0.4^{**}$

* taken from MWH (2005) and Voutchkov (2012, 2017a)

** assumed values

*** determined from R_c model equation from (5.1)

Column diameter of filter system ~ 2.0m (typical value for large-scale pre-treatment facilities)

TABLE 7

Run	c_0^* (kg/m ³)	d_p^* (μ m)	V_s (m/h)	$d_{c,0}$ (mm)	ε_0^*	L_m (m)	$\eta\%$	α'_{48}	α'_p at 48h (kwh/m ³)	t_b (h)
A	0.004	20	5.0	0.15	~0.3	1.5	~100%	2.58 (> 1)	38.9	18.9
B	0.004	20	5.0	0.30	~0.4	1.5	~100%	0.243	3.67	193
C	0.004	20	5.0	0.50	~0.4	1.5	~100%	0.215	3.24	314
D	0.100	20	5.0	0.15	~0.3	1.5	~100%	93.8 (>1)	1410	0.8
E	0.100	20	5.0	0.30	~0.4	1.5	~100%	7.45 (>1)	112	7.73
F	0.100	20	5.0	0.50	~0.4	1.5	~99.8%	4.48 (>1)	67.6	12.6

$d_p = 20\mu\text{m}$, $\rho_p = 1050\text{kg/m}^3$, $\mu_{in} = 0.89 \times 10^{-3}\text{kg/ms}$

*assumed values

Column diameter of filter system ~ 2.0m (sufficiently large for pre-treatment filters)

TABLE 8

Run	c_0^{**} (kg/m ³)	V_s^* (m/h)	L_m (1) (m)	L_m (2) (m)	α'_{48} (1)	α'_p at 48h (1) (kwh/m ³)	ε_c at 48h (1)	t_b (h) (1)
1	0.004	5.0	1.0	0.8	0.00780	0.0784	0.498	2580
2	0.004	7.5	1.0	0.8	0.0179	0.180	0.497	1300
3	0.004	10.0	1.0	0.8	0.0324	0.326	0.496	777
4	0.004	5.0	1.1	0.7	0.00630	0.0697	0.498	2840
5	0.004	7.5	1.1	0.7	0.0119	0.132	0.498	1420
6	0.004	10.0	1.1	0.7	0.0242	0.268	0.497	855
7	0.004	5.0	1.2	0.6	0.00480	0.0579	0.499	3100
8	0.004	7.5	1.2	0.6	0.0110	0.133	0.498	1550
9	0.004	10.0	1.2	0.6	0.0199	0.240	0.497	933
10	0.004	5.0	1.3	0.5	0.00442	0.0578	0.499	3350
11	0.004	7.5	1.3	0.5	0.0101	0.131	0.498	1680
12	0.004	10.0	1.3	0.5	0.0183	0.239	0.497	1010
13	0.004	5.0	1.4	0.4	0.00410	0.0577	0.499	3610
14	0.004	7.5	1.4	0.4	0.00939	0.132	0.498	1810
15	0.004	10.0	1.4	0.4	0.0169	0.238	0.497	1090
16	0.100	5.0	1.0	0.8	0.230	2.31	0.454	103
17	0.100	7.5	1.0	0.8	0.600	6.03	0.431	51.8
18	0.100	10.0	1.0	0.8	1.23 (> 1)	12.4	0.409	32.0
19	0.100	5.0	1.1	0.7	0.205	2.27	0.458	113
20	0.100	7.5	1.1	0.7	0.517	5.72	0.438	57.0
21	0.100	10.0	1.1	0.7	1.06 (> 1)	11.7	0.417	34.2
22	0.100	5.0	1.2	0.6	0.181	2.18	0.462	124
23	0.100	7.5	1.2	0.6	0.461	5.56	0.443	62.2
24	0.100	10.0	1.2	0.6	0.931	11.2	0.424	37.3
25	0.100	5.0	1.3	0.5	0.164	2.14	0.465	134
26	0.100	7.5	1.3	0.5	0.418	5.46	0.447	67.4
27	0.100	10.0	1.3	0.5	0.826	10.8	0.430	40.4
28	0.100	5.0	1.4	0.4	0.153	2.15	0.467	144
29	0.100	7.5	1.4	0.4	0.388	5.46	0.450	72.5
30	0.100	10.0	1.4	0.4	0.744	10.5	0.435	43.5

$d_p = 100\mu m$, $\rho_p = 1050 kg/m^3$, $\mu_{in} = 0.89 \times 10^{-3} kg/ms$

(1) – anthracite: $d_{c,0} = 1mm^*$, $\varepsilon_0 = \sim 0.5^*$

(2) – sand: $d_{c,0} = 0.6mm^*$, $\varepsilon_0 = \sim 0.4^*$

*taken from MWH (2005) and Voutchkov (2012, 2017a)

**assumed values

Column diameter of filter system ~ 2.0m (sufficiently large for pre-treatment filters)

TABLE 9

Run	c_0^{**} (kg/m ³)	d_p^{**} (μm)	V_s^* (m/h)	$d_{c,0}^*$ (1) (mm)	ε_0^{**} (1)	$d_{c,0}^*$ (2) (mm)	ε_0^{**} (2)	$\eta\%$ at 48h (1)	$\eta\%$ at 48h (2)	α'_{48} (1)	α'_p at 48h (1) (kwh /m ³)	α'_{48} (2)	α'_p at 48h (2) (kwh /m ³)	α'_{48} (1+2)	t_b (h) (1)
A	0.004	20	10.0	0.9	~0.5	0.55	~0.4	57.5%	30.9%	0.0541	0.762	0.627	2.52	0.681	465
B	0.004	20	10.0	0.8	~0.5	0.50	~0.4	70.0%	24.8%	0.0740	1.04	0.538	2.16	0.612	420
C	0.004	20	10.0	0.7	~0.4	0.40	~0.4	88.9%	10.7%	0.411	5.79	0.296	1.19	0.707	102
D	0.100	20	10.0	0.9	~0.5	0.55	~0.4	56.6%	29.8%	1.55	21.8	25.4 (>1)	102	27.0 (>1)	18.6
E	0.100	20	10.0	0.8	~0.5	0.50	~0.4	69.2%	24.4%	2.21	31.1	20.5 (>1)	82.5	22.7 (>1)	16.8
F	0.100	20	10.0	0.7	~0.4	0.40	~0.4	86.6%	12.8%	15.0 (>1)	211	10.8 (>1)	43.4	25.8 (>1)	4.09

$d_p = 20\mu m$, $\rho_p = 1050 kg/m^3$, $\mu_{in} = 0.89 \times 10^{-3} kg/ms$

(1) – anthracite: $L_m = 1.4m$

(2) – sand: $L_m = 0.4m$

*taken from MWH (2005) and Voutchkov (2012, 2017a)

**assumed values

Column diameter of filter system ~ 2.0m (sufficiently large for pre-treatment filters)

TABLE 10

Run (Single-media)	t_b (h)	γ (Single-media)	Run (dual-media)	t_b (h)	γ (Dual-media)
1 (Table 6)	624	4.21	1 (Table 8)	2580	18.2
2 (Table 6)	300	2.02	2 (Table 8)	1300	8.95
3 (Table 6)	179	1.31	3 (Table 8)	777	5.15
4 (Table 6)	850	5.27	4 (Table 8)	2840	20.3
5 (Table 6)	410	2.36	5 (Table 8)	1420	9.87
6 (Table 6)	244	1.61	6 (Table 8)	855	5.61
7 (Table 6)	1130	7.04	7 (Table 8)	3100	22.1
8 (Table 6)	546	3.15	8 (Table 8)	1550	10.8
9 (Table 6)	326	1.72	9 (Table 8)	933	6.28
10 (Table 6)	1360	8.76	10 (Table 8)	3350	23.8
11 (Table 6)	655	3.58	11 (Table 8)	1680	11.8
12 (Table 6)	390	2.03	12 (Table 8)	1010	6.87
13 (Table 6)	1710	10.9	13 (Table 8)	3610	25.8
14 (Table 6)	819	4.44	14 (Table 8)	1810	12.4
15 (Table 6)	488	2.38	15 (Table 8)	1090	7.17

*Run A from Table 8 provides no energy cost savings as breakthrough occurs before the 48h time mark.