Desalination and Water Treatment
www.deswater.com

1944-3994/1944-3986
doi: 10/5004/dwt.2012.3468

45 (2012) 276–283
July

A statistical approach to analyze factors affecting silt density index

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Received 10 October 2011; Accepted 6 November 2011

ABSTRACT

Silt Density Index (SDI) has been used as the most popular fouling index for reverse osmosis (RO) feed water to select a proper pretreatment option for RO processes. However, SDI lacks the fundamental consideration of RO membrane fouling, because SDI is supposed to be only sensitive to particles larger than 0.45 μm in diameter while fine particles (which can pass through a 0.45 μm filter) and dissolved organic matters can be potent foulants for RO processes. Our study started from the suspected performance of SDI based on its lack of the fundamental basis. Various sources of SDI data from nine literatures were collected and analyzed with turbidity and dissolved organic carbon (DOC). Interestingly, the result of our study shows that SDI can express the amount of particulate and organic fouling together. SDI can be described as a function of turbidity, DOC, and a categorical binary variable, M, for pretreatment type (i.e., $M = 1$ for membrane filtration and $M = 0$ for other methods). SDI increases if either of turbidity or DOC becomes higher and membrane filtration is not used as a pretreatment option according to the multiple linear regression method using various data sources. Therefore, our study concludes that SDI can measure the potential of fouling effectively.

Keywords: Silt density index (SDI); Dissolved organic matter; Turbidity; Reverse osmosis (RO); Fouling

1. Introduction

Membrane filtration has been spotlighted as a technology capable of overcoming the scarcity of water resources resulting from global climate change and environmental pollution. However, fouling resistibility is always the concern when seeking to enhance the efficiency of membrane filtration technology. Generally, pretreatment coupled with periodic backwashing is used to reduce fouling resistibility. Because reverse osmosis (RO) processes require a high pressure under which to operate, pretreatment is more preferred over backwashing to reduce fouling resistibility. Selecting an appropriate pretreatment system has been one of the most important design factors for RO processes and it is still the most concern of RO system engineers and researchers recently [1–5].

Silt Density Index (SDI) is generally used as a standard of the RO feed water quality [6]. A SDI test of a dead-end filtration unit with 0.45 μm membrane requires

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an operating pressure of 206.8 kPa. The SDI result is calculated as described below [7]:

$$\mathrm{SDI}_T = \frac{100\left[1-\dfrac{t_i}{t_f}\right]}{T} \tag{1}$$

where, t_i is the time required to filter 500 ml upon the start-up of the test, and t_f is the time required to filter 500 ml after a typical period, T in this case (i.e., 5, 10 or 15 min) from the point of finishing the measurement of t. When the SDI value exceeds the standard values, which are generally 3 to 5 depending on the site conditions, the water quality is unsuitable for RO feed water [7].

The most powerful advantage of SDI is that it is relatively simple to be measured, which makes SDI the most popular fouling index for RO feed water. However, the concentration of silt or suspended solids, which is represented by SDI, has a weak relationship with the fouling of RO membrane. A 0.45 μm filter is used to measure SDI, though the materials which cause fouling in the RO process are organic materials or nanoparticles smaller than 0.45 μm [8–10]. This has been considered as the most serious weakness related to the use of SDI as a fouling index. Therefore, studies have tried to solve this weakness of SDI and find a realistic index for fouling [11]. Schippers and Veerdow [12] suggested a membrane fouling index (MFI) and as an extension, MFI-UF and MFI-NF has been suggested as indices for fouling caused by fine particles and organic materials [13,14]. Chon et al. [15] developed organic fouling indices of nanofiltration membrane for wastewater reclamation.

Kim et al. [16] proposed an independent index in an effort to find a membrane with high resistance against fouling. This method was not a series of SDI or MFI that accesses the quality of the pretreated feeding water. This independent index arises from the fact that fouling is affected by the force of the physicochemical interaction between the surface of the membrane and pollutants [17,18]. Thus, many indices have been proposed to address the weaknesses of SDI, though they are still at the research level with limited field applications. Given the fact that SDI has abundant data because it has been used for a long time with fewer alternatives, field operators prefer to use SDI over other suggested indices. Thus, SDI is still used in the field as a fouling index to access the pretreated water quality for RO feed, though it has been nearly 30 y since the issue of weaknesses of SDI was originally raised.

This study gives careful consideration to SDI by asking two conflicting questions. First, though SDI has an intrinsic weakness, is SDI used for RO fouling just because there are fewer alternatives? Second, are there any evidences to dissipate the weakness of SDI so that we can use SDI as a useful index in practice? In order to derive the answers to these two questions, this study used a statistical approach to relate SDI to water quality parameters for RO fouling.

RO fouling can be categorized into particulate fouling, organic fouling, and biofouling. Concentrations of particles, organic matter, microorganisms are water quality parameters for particulate fouling, organic fouling, and biofouling, respectively. The concentration of microorganisms should be included in that of particles because microorganisms are micron-sized. Turbidity is a water quality parameter to represent the concentration of particles and dissolved organic carbon (DOC) concentration represent that of organic matter. Thus these two parameters were selected as water quality parameters for RO fouling.

It would be better to select more parameters related to biofouling. However biofouling is rather complex phenomenon which cannot be explained by one or two parameters and it is very challenging to make a representative index for biofouling. Since fouling indices are for selecting pretreatment methods for the RO process, it may not be useful to make fouling indices for biofouling because the only way to avoid biofouling is disinfection. The other reason of selecting turbidity and DOC is the availability to obtain the data from the real field application. Therefore, this study undertook a correlation analysis and a regression analysis using turbidity and DOC as a predicting variables for SDI.

2. Methods

2.1. SDI data collection

SDI data were selected from research reports [19–21] and papers [22–27] containing SDI, turbidity and DOC data in various RO plants as shown in Table 1. Thus, the results of statistical analysis are not supposed to be biased. The collected data from nine different references include the following information: six types of raw water, nine pretreatment options including no pretreatment, turbidity ranged of 0.08 to 2.0, DOC ranged of 0.4 to 8.0, and SDI ranged of 0.1 to 6.67.

2.2. Statistical approach

Statistical approach is very useful to derive important information from the raw data and it has been used to interpret the relationship among membrane experimental parameters [28,29]. In this study, we investigated the statistical relationship between the water quality index (e.g., the turbidity, concentration of DOC) of RO feed water and SDI using a correlation analysis and a multiple regression analysis [30]. The correlation analysis was conducted to quantify the strength of the linear relationship between the two variables – turbidity

Table 1
SDI data used in this study

Raw water	Pretreatment	Turbidity	DOC	SDI	Reference
Deep seawater	–	0.1–0.35	0.79–1.03	0.1–4.9	[19–21]
Lake water	Coagulation-sedimentation	0.12–2.0	2.0–5.0	> 6.67	
	MF[a]	0.07–0.14	6.0–8.0	1.27–3.26	
	Fiber filter	0.16–0.43	3.1–4.5	3.3–6.4	
Wastewater effluent	UF[b]	0.16–0.18	6.3–7.0	2.6–2.9	
Drinking water	–	0.13	1.4–2.0	2.1	
Seawater	–	>0.22	N.A.	>6.67	[22]
Seawater	UF	0.2–0.4	N.A.	0.4–1.8	[23]
Wastewater effluent	UF	0.12–0.14	N.A.	1.1–2.1	[24]
Brackish water	CAPS[c]	0.08	8	4.6	[25]
Seawater	UF	0.05–0.2	0.4–2.0[d]	1.2–3.0	[26]
Seawater	DMF[e] (5 m h^{-1})	0.3	N.A.	5.2–5.3	[27]
	Coagulation–DMF (5 m h^{-1})	0.1	1.9–2.2	3.4	
	Coagulation-DMF (10 m h^{-1})	0.1	1.4–2.8	4.4	

[a]Microfi ltration.
[b]Ultrafi ltration.
[c]Compact accelerated precipitation softening.
[d]Calculated values using the relationship between chemical oxygen demand (COD) and DOC; DOC = COD × 12/32.
[e]Duel media fi lter.

versus SDI and the concentration of DOC versus SDI. The Pearson correlation is some value between −1 and 1. As it approaches zero there is less of a relationship (closer to uncorrelated). The closer the coefficient is to either −1 or 1, the stronger the correlation between the variables. Pearson's correlation coefficient (r) is calculated as shown in Eq. (2):

$$r = \frac{n\left(\sum XY\right) - \left(\sum X\right)\left(\sum Y\right)}{\sqrt{\left\{n\sum X^2 - \left(\sum X\right)^2\right\}\left\{n\sum Y^2 - \left(\sum Y\right)^2\right\}}} \tag{2}$$

where, X and Y are the explanatory variables and n is the size of the sample.

Multiple linear regression attempts to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to the collected data. Formally, the model for multiple linear regression, given n data, is as follows:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i \quad \text{for } i = 1, 2, \ldots, n \tag{3}$$

where, x_{ij} denotes the ith data on the jth independent variable, p is the number of independent variables, β_j represents the parameter of the population regression line for x_{ij}, and ε_i is error for the prediction.

In order to get the β_j parameters to minimize the sum of squares for the error (SSE), the normal equation in matrix notation is derived such as:

$$(X^T X)\hat{\beta} = X^T Y \tag{4}$$

where $\hat{\beta}$ and Y are column vectors with the estimated β_j values denoted by $\hat{\beta}_i$ and y_i, respectively, X is a matrix with elements denoted by x_{ij}. Thus X, Y, and $\hat{\beta}$ are $n \times p$, $n \times 1$, and $p \times 1$ matrices, respectively. The solution of Eq. (4) is described as:

$$\hat{\beta} = (X^T X)^{-1} X^T Y \tag{5}$$

Mean square error (MSE, $\hat{\sigma}^2$) of the estimation can be calculated using SSE such as:

$$\hat{\sigma}^2 = \text{MSE} = \frac{\text{SSE}}{n-p-1} = \frac{1}{n-p-1}\sum_{i=1}^{n} \varepsilon_i^2 = \frac{1}{n-p-1}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{6}$$

The standard error of $\hat{\beta}_i$ is $\hat{\sigma}^2$ multiplied by the square root of the ith diagonal element of the matrix $(X^T X)^{-1}$, which can be computed by Microsoft Office Excel. The standard error of a parameter is used to obtain the confidence interval of the parameter in order to check the statistical significance of the parameter. If the confidence interval includes zero, the parameter is regarded as the statistically insignificant one.

The statistics considered in the analysis include the R^2 value, a t-test and F-tests. The R^2 and F values provide insight into the quality of each model. The R^2 value indicates the overall predictive power of the model. The t-test determines the predictive power of each variable. The R^2 value and the F statistic are calculated as shown in Eqs. (7) and (8), respectively:

$$R^2 = 1 - \frac{\text{SSE}}{\text{SST (total sum of squares)}} \tag{7}$$

$$F = \left[\frac{\text{SSR (regression sum of squares)}}{p}\right]/\text{MSE} \tag{8}$$

Here, we attempted to build the best model with SDI as a dependent variable and the turbidity of the RO feed water and concentration of DOC in the RO feed water as explanatory variables (i.e., independent variables). A full quadratic function of the turbidity and DOC was constructed. The order of the function was limited to second-order terms to avoid model complexity due to a large number of variables. A statistically significant model was selected through an F-test and a t-test of the regression equation as derived from the data.

Progressive model enhancement was conducted via the following steps. First, the process starts with the most complicated model, after which a parameter, if not statistically significant, is dropped to make a modified model. The statistical significance of a parameter is estimated using the 95% confidence interval of the parameter as explained earlier.

Subsequently, a regression analysis is conducted with the modified model. This process is iterated until a statistically significant model is built. According to the order of dropping a parameter, several numbers of statistically significant models can be obtained.

Finally, the most suitable model is selected among the statistically significant models according to the conditions for a better model. The regression model is considered as a better model in terms of two aspects, a higher R^2 and a smaller number of variables.

3. Results and discussion

3.1. Relationship between SDI and other water quality parameters

In general, the higher the concentration of suspended particles, the more SDI is expected to increase. Fig. 1 shows the relationship between SDI and turbidity.

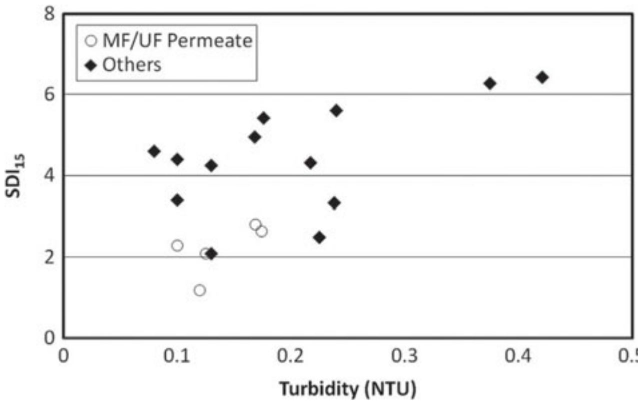

Fig. 1. Relationship between SDI and turbidity.

The results show a weak positive correlation, 0.607, between the Pearson's correlation coefficient of SDI and turbidity in the RO feed water, regardless of the type of pretreatment process (without distinction of ◆ or ○). Though these results are predictable because the SDI is affected by particles which are larger than 0.45 µm, the weak relationship must be noted.

Additionally, as shown in Fig. 1, SDI is lower when membrane filtration (i.e., MF or UF) is used as a pretreatment process (marked as ○) relative to other methods (no pretreatment or methods without MF/UF, marked as ◆). From these results, we can predict that there are more water quality parameters that affect SDI besides turbidity. As discussed earlier, DOC was selected one of water qualities affecting RO membrane fouling. Therefore, the relationship between the concentration of soluble organics DOC and SDI was analyzed.

If SDI is not affected by DOC, SDI is intrinsically weak as an index of RO fouling, as soluble organics are known to have a considerable effect on RO fouling [17,18]. DOC is measured as the following order: (1) filter the water sample through a 0.45 µm filter, (2) oxidize the filtered water by combustion or physicochemical methods to change organic carbon into inorganic carbon, (3) measure the concentration of inorganic carbon sources, and (4) converge the concentration based on carbon.

Theoretically, DOC should not have any relationship with SDI, which is measured using the same pore size filter (i.e., 0.45 µm). As shown in Fig. 2, regardless of the pretreatment (without the distinction of ◆ or ○), the DOC concentration of the RO feed water and the Pearson's correlation coefficient of SDI has a weak positive correlation of 0.223. In other words, there is little relationship between DOC and SDI as expected from the theoretical point of view. However this result does not mean that we should exclude DOC from the list of water quality parameters affecting SDI. Instead, we investigated the cooperative effect of turbidity and DOC by using a

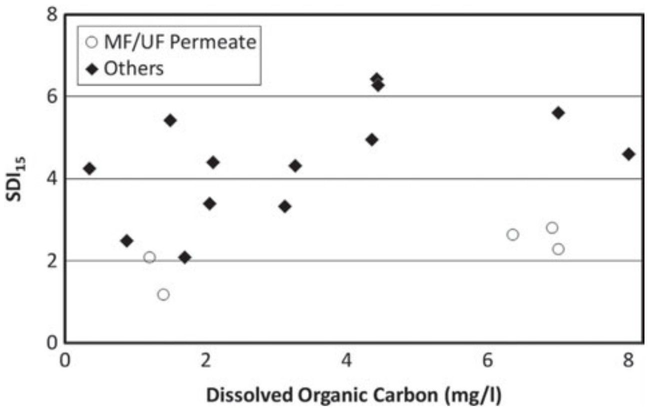

Fig. 2. Relationship between SDI and DOC.

multiple regression analysis. In addition, both Figs. 1 and 2 show that a pretreatment with MF/UF results in a lower SDI than the other methods, which will be reflected for the multi-regression method.

3.2. Empirical model building by multiple linear regression analysis

A multi-regression analysis was conducted to analyze the effects of turbidity and DOC on SDI. To minimize the complexity of the model, a full quadratic function of turbidity (t in Table 2) and the DOC concentration (d in Table 2) was set to have the second degree as the maximum degree. The model was constructed by eliminating parameters which have less importance one by one from the most complicated model. A statistically insignificant parameter was dropped to obtain a good regressive (i.e., statistically significant) model as explained in the method section. The models E, F and G were the satisfied regression model. Among these models, model E was the optimal model, having the highest R^2 value. The equation of the model E is shown below:

$$\mathrm{SDI} = 2.93 + 21.2 \times (\mathrm{Turbidity})^2 \tag{9}$$

where, the unit of turbidity is NTU.

Eq. (9) relates SDI to the turbidity squares only. The R^2 value of 0.396 reflects the slight predictive power of the model, indicating that the predicted values do not follow the actual data closely. Accordingly, another approach is needed.

From Figs. 1 and 2, we focused on the fact that SDI was remarkably low when using membrane filtration (i.e., MF or UF) as a pretreatment method. Therefore a categorical binary variable, M, was added to the analysis. $M = 1$ denotes the adoption of membrane filtration as a pretreatment method, with the others being $M = 0$. The same procedure to find the optimal model as shown in Table 2 was carried out using M, turbidity and the concentration of DOC. The regression results were listed in Table 3.

The models E, F and G satisfied the conditions of a good regressive model because these models did not have statistically insignificant parameters, the 95% confidence interval of which included zero. Model E had

Table 2
Summary of all possible regressions for the SDI model using turbidity (t) and DOC (d)

Model	Coefficient of the term (parameters for the regression)						R^2	F statistic (significant F)
	a_0	a_1t	a_2d	a_3t^2	a_4d^2	a_5td		
A	3.50	–6.10	–0.113	24.2	0.00718	1.01	0.425	1.78
[interval][a]	[–2.3,9.3]	[–51.3,39.1]	[–2.2,2.0]	[–52.7,101.2]	[–0.2,0.2]	[–4.9,6.9]		[0.193]
B	3.44	–6.20	0.0463	24.5	–	0.959	0.425	2.40
[interval]	[–1.8.8.7]	[–49.1,36.8]	[–0.9,0.8]	[–48.6,97.5]		[–4.5,6.5]		[0.103]
C	3.24	–4.94	–	24.4	–	0.675	0.424	3.44
[interval]	[–0.4,6.8]	[–39.8,29.9]		[–45.5,94.4]		[–1.1,2.5]		[0.0463]
D	2.75	–	–	15.0	–	0.639	0.420	5.44
[interval]	[1.7,3.7]			[–6.7,36.7]		[–1.1,2.4]		[0.0167]
E	2.93	–	–	21.2	–	–	0.396	10.49
[interval]	[2.1,3.8]			[7.31,35.0]				[0.00513]
F	1.97	10.1	–	–	–	–	0.369	9.34
[interval]	[0.5,3.4]	[3.1,17.1]						[0.00755]
G	2.75	–	–	–	–	1.54	0.336	8.10
[interval]	[1.7,3.8]					[0.4,2.7]		[0.0116]

[a]95% confidence interval.

Table 3
Summary of all possible regressions for the SDI model using pretreatment type (M), turbidity (t) and DOC (d)

Model	Coefficient of the term (parameters for the regression)							R^2	F statistic (significant F)
	a_0	a_1M	a_2t	a_3d	a_4t^2	a_5d^2	a_6td		
A	5.18	−2.20	−14.0	−0.294	21.0	0.0181	2.39	0.768	6.08
[interval][a]	[1.2,9.2]	[−3.4,-1.0]	[−44.5,16.6]	[−1.7,1.1]	[−30.6,72.5]	[−0.1,0.2]	[−1.6,6.4]		[0.00506][b]
B	5.01	−2.20	−14.2	−0.125	21.5	–	2.27	0.767	7.88
[interval]	[1.4,8.6]	[−3.3, −1.1]	[−43.2,14.9]	[−0.7,0.4]	[−27.4,70.4]		[−1.5,6.0]		[0.00170][b]
C	4.46	−2.18	−11.0	–	21.4	–	1.50	0.762	10.4
[interval]	[2.0,6.9]	[−3.3, −1.1]	[−34.3,12.9]		[−25.6,68.4]		[0.2,2.8]		[0.000527][b]
D	3.47	−2.19	−0.691	–	–	–	1.56	0.744	13.6
[interval]	[2.3,4.7]	[−3.3, −1.1]	[−9.0,7.6]				[0.3,2.8]		[0.000198][b]
E	3.39	−2.15	–	–	–	–	1.48	0.744	21.8
[interval]	[2.7,4.1]	[−3.1, −1.2]					[0.7,2.2]		[0.0000367][b]
F	2.47	−2.08	6.38	–	–	–	0.205	0.713	11.6
[interval]	[1.2,3.8]	[−3.2, −0.9]	[0.9,11.9]				[0.0,0.4]		[0.000435][b]
G	4.01	−2.11	−4.01	−0.123	–	–	2.32	0.749	9.68
[interval]	[1.3,6.8]	[−3.3, −1.1]	[−21.4,13.4]	[−0.7,0.4]			[−1.4,6.0]		[0.000741][b]

[a]95% confidence interval.
[b]Probability that the linear regression is not satisfied statistically.

the minimum numbers of variables and the maximum R^2 value was found in model G. However, the increase in R^2 of model G compared to model E is so little (i.e., 0.005) that it was considered safe to conclude that the best one is model E:

$$\text{SDI} = 3.39 - 2.15 \times \text{M} + 1.48 \times \left(\text{Turbidity}\right) \times (\text{DOC}) \quad (10)$$

where, the unit of DOC and turbidity is mg l^{-1} and NTU, respectively.

According to the best model depicted in Eq. (10), DOC and turbidity both affect SDI (e.g., if DOC is high and even when turbidity is low, SDI remains high); in addition, the R^2 value is 0.744, which means that the model is reliable. Specifically, the role of M is significant in SDI. The coefficient of M is −2.15, which means pretreated water with membrane filtration has a decreased SDI value by about 2.15 compared to that with other methods (including no pretreatment) even if the treated water turbidity and DOC are the same. Thus, the model implies that the fouling potential of pretreated water with membrane filtration is lower than that with other methods.

In the result of the F-test hypothesis, the probability of Eq. (10) for the statistical acceptance of the linear regression was higher than 99.9% (i.e., 1 − 0.0000367 = 0.9999633) according to the match with the regression equation. In the result of the t-test hypothesis, each probability of the coefficients of model E was higher than 99.9%, showing statistical significance, which shows that SDI was co-affected by DOC and turbidity at least.

From the model of Eq. (10), two questions arise. First, why do dissolved organic matters smaller than 0.45 µm deposit onto the pore structure, which leads a high SDI value? Second, what makes the SDI value of pretreated water by membrane filtration smaller than that by other pretreatment methods?

Fouling mechanisms of the SDI filter include pore blocking, cake formation and pore constriction as shown in Fig. 3, which is an edited figure from the original one [31]. From these mechanisms, organics are considered to

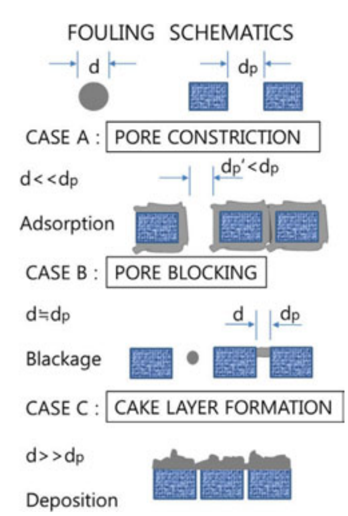

Fig. 3. Mechanism of SDI filter fouling: (a) pore constriction (affected by organic matters and fine particles), (b) pore blocking (affected by particles) and (c) cake formation (affected by the particles).

be a source of resistance (i.e., port construction) when they are adsorbed in the pore space of the SDI filter. If the concentrations of fine particles (which can penetrate into the SDI filter) and organic matters are both high, the possibility of pore constriction will increase. There are more chances of high concentration of fine particles when turbidity is high. This is the reason why the water with high turbidity and DOC exhibits a higher SDI value as described in the best regression model of Eq. (10).

According to Eq. (10), the SDI value decreases when the membrane filtration pretreatment is used. The pore sizes of MF or UF membranes (<0.1 μm) are much smaller than the pore size of the SDI testing filter (≈0.45 μm). Although DOC is not effectively removed by MF or UF membranes, the fine particles in a range of 0.1–0.45 μm of diameter will be effectively rejected by the membranes. As discussed earlier, both fine particles and DOC make the SDI value increase. The lack of these fine particles which are not easily detected by turbidity meters could be the most probable cause of the reduction of SDI by using membrane filtration as a pretreatment method.

4. Conclusions

Silt density index (SDI), the acronym for the SDI, has been the most popular fouling index for RO feed water regardless of the lack of its theoretical base argued by many researchers. We performed the statistical analysis using SDI and the water quality parameters affecting RO membrane fouling in order to answer the following question: Do we have to use SDI despite of its intrinsic weakness just because there are fewer alternatives? If the answer to this question is "No," we researchers should insist that the field operators should not use SDI as a fouling index for RO feed water. Fortunately, the answer is "Yes" according to our results of the statistical analysis.

SDI can be described as a function of turbidity, DOC, and a categorical binary variable, M, for pretreatment type (i.e., $M = 1$ for membrane filtration and $M = 0$ for other methods). This implies that SDI values can express the amount of particulate and organic fouling, because turbidity and DOC are good indicators of particulate and organic fouling, respectively. This is an interesting result because there are few literatures to report that SDI is affected by DOC. Moreover, the use of membrane filtration as a pretreatment option significantly decreases the SDI value in our regression model equation, which also implies low SDI values exhibit low fouling potential of RO membrane (We should consider that membrane filtration is one of the most effective pretreatment methods in the market.). Therefore, it is concluded that SDI can measure the potential of membrane fouling more effectively than expected from its lack of the fundamental consideration of RO membrane fouling.

Acknowledgement

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (Grant No. 2011-0014006).

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