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The Effects of Various Factors on Ballast Water Treatment Using Crumb Rubber Filtration: Statistic Analysis

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ABSTRACT

Removal of turbidity, phytoplankton, and zooplankton from ballast water with waste-tire-made crumb rubber filtration was evaluated in this study. The influences of various design, operational, and water quality parameters (filter depth, media size, filtration rate, temperature, turbidity, running time, etc.) on filtration performance were investigated. Statistical approaches were used to develop empirical models, including a head loss model which partially resembles the Kozeny equation, to evaluate these factors. Regression models, validated with data from the field study, were used for predicting the influence of operational parameters on crumb rubber filtration. Sensitivity analyses of the significance of each factor were conducted. Results showed that media size played a very important role in the removal of suspended matter, while temperature, filter depth, influent turbidity, and running time did not have a significant influence. Head loss was most affected by filtration rate and media size. These results indicated that the behaviors of the crumb rubber filtration for ballast water treatment cannot be described by the theories and models for conventional granular media filtration without modification.

Key words: ballast water; crumb rubber; filtration; plankton; waste tires

INTRODUCTION

Ballast water is commonly used to stabilize vessels during voyage. The uptake, transport, and subsequent discharge of ballast water cause the transport of aquatic organisms around the world. The introduction of alien aquatic species caused by the uncontrolled discharge of ballast water has created great physical, ecological, and economical impacts on the aquatic environment (National Research Council, 1996; Parson and

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Harkins, 2002; Bax *et al.*, 2003). For example, Buck (2004) reported that there was an annual loss up to 5,000 million dollars from damage by Zebra Mussels to water pipes, boat hulls, and other hard surfaces in the Great Lakes. The invasion of alien species, for example, the American Atlantic coast comb jelly fish, Asian clam, and European crab, have caused the collapse of fisheries in various regions (National Research Council, 1996; Bax *et al.*, 2003). In addition, the introduction of pathogenic bacteria and viruses can negatively impact health of human and fish species. Ruiz *et al.* (2001) estimated that the annual economic impact of the invasive species in the United States alone exceeded 100 billion dollars. The newly adopted international Ballast Water Convention sets maximum concentrations of 10 viable organisms per cubic meter for organisms larger than 50 μm and 10 viable organisms per milliliter for organisms larger than 10 μm and less than 50 μm in the minimum dimension (International Maritime Organization, 2004). The convention also sets standards for indicator microbes, including *Vibrio cholerae, Escherichia coli*, and Intestinal Enterococci.

There are many options for ballast water treatment, for example, ocean exchange, UV irradiation, biocides, thermal treatment, etc. The National Research Council (1996) evaluated a variety of approaches for treating ballast water and recommended filtration as the most promising technology. Based on present technology, Peraki and Yang (2003) also reported that filtration followed by UV is one of the best available technologies for treating ballast water. Traditional granular media (e.g., sand and anthracite) filtration can effectively remove a majority of particulates and organisms found in ballast water, especially for those larger than 50 μm (Kazumi *et al.*, 2004), but this technology might not be economically and technologically feasible for shipboard ballast water treatment because of its relatively high density, low filtration rate, and large space requirements. A filter with low density media and high filtration rate is needed for shipboard ballast water treatment.

Because of the increasing number of waste tires in stockpiles, the management and recycle of waste tires are of great concern (U.S. EPA, 1993; Rubber Manufactures Association, 2002; Sunthonpagasit and Hickman, 2003). Reuse of scrap tires for various applications has been recommended to conserve natural resources and minimize environmental impacts. An innovative filtration technology, using crumb rubber produced from waste tires as filter media, has been developed at Penn State Harrisburg to treat wastewater (Graf and Xie, 2000; Xie *et al.*, 2001). The side-by-side comparison between traditional sand/anthracite granular media filters and the crumb rubber filter indicated that the crumb rubber filter allows higher filtration rate and longer filter run time (Xie *et al.*, 2001; Hsiung, 2003). Its relatively low density and compact size require less space, and allow for potential shipboard installation and operation.

Operation of a granular media filter is influenced by many factors, including media properties, filter design conditions, and water quality. An improved understanding of parameters that influence filter performance has led to improved design and operation of granular media filters (Cleasby and Logsdon, 1999). Also, numerous filtration and head loss models have been developed for conventional granular media filters (Cleasby and Logsdon, 1999). However, crumb rubber filtration is different from conventional granular media filtration for water and wastewater treatment. For example, the elasticity of the crumb rubber media results in filter compression during filtration and reduces filter media porosity. In addition, ballast water filtration generally relies on physical straining and collection, while typical granular media filtration removes destabilized particles from pretreated water. Consequently, traditional models that have been developed for granular media filtration may not be easily applied to crumb rubber filtration of typical ballast water.

Statistical analyses have been used widely to elucidate the impacts of various parameters on system behaviors (Dean and Voss, 2000; Sutherland *et al.*, 2001). Garcia-Villanova *et al.* (1997) used regression techniques to correlate trihalomethane formation potentials with water-quality parameters, and the results showed good correlation. Abdul-Wahab *et al.* (2005) used multiple regression analysis to fit ozone concentrations using pollutant and meteorological variables as predictors, and the resulting model clearly revealed the significance of these variables. It was hypothesized that statistical analysis could be a suitable tool for modeling crumb rubber filtration for ballast water treatment until a more suitable mechanistic approach is developed.

The objectives of this study were to evaluate crumb rubber filtration with chemically untreated lake water (typical of a fresh water ballast tank supply), and develop a model that can aid in the design and operation of a crumb rubber ballast water filter.

MATERIALS AND METHODS

Design and operational conditions

The pilot study was carried out at Gifford Pinchot State Park, Pennsylvania, USA, where lake water was used to simulate a ballast water supply. Three levels (high, medium, and low) of crumb rubber media sizes, filter depths, and filtration rates, were investigated. Three filters with 5-cm internal diameter were loaded with different size crumb rubber media (0.66, 1.2, or 1.9 mm effective size). Specific weight of the crumb rubber media was about 1,130 kg/m^3. Filter depths were 0.6, 0.9, and 1.2 m. Filtration rates were 24.4, 48.9, and 73.3 m^3/hour·m^2 (10, 20, and 30 gpm/ft^2). Influent water head was kept stable at 4 meters. In each filtration run, three filters with different media size were run simultaneously for 8 h under the same operational conditions, including filter depth, filtration rate, and influent water quality, which means that one run included three subexperiments (three filters with different media sizes). A total of nine filtration runs were conducted in this study. Therefore, 27 subexperiments were conducted totally, described by a 3 × 3 matrix (three factors × three levels). Air scouring plus water backwash was used to regenerate the filters after 8-h filtration runs. The details of the experimental conditions have been reported by Tang *et al.* (2005).

Data collecting

Field sample analysis indicated that almost all of the organisms in the size range 10–50 μm in minimum dimension were phytoplankton, while almost all organisms in the size range ≥50 μm in minimum dimension were zooplankton. Therefore, organisms were categorized and reported as phytoplankton with size 10–50 μm in minimum dimension and zooplankton with size ≥50 μm in minimum dimension. Phytoplankton enumeration was conducted with a clear 1-mL counting cell and a compound microscope (100×). Zooplankton was concentrated with a 50-μm plankton net, then transferred into a clear 5-mL counting cell and counted using a stereoscopic microscope (10× to 60×). Turbidity was measured by a potable turbidity meter (0.01–1,000 nephelometric turbidity unit or NTU).

In each experiment, filters were operated for 8 h. For each 8-h run, five samples were measured for turbidity, phytoplankton, and zooplankton, and head loss at run times of 0.5, 2, 4, 6, and 8 h. In this paper, the removal efficiency with each targeted parameter was the average value of these five data points. But for statistical analysis, individual data points were used instead of average values.

Statistical regression analysis

Sigma Plot (SPSS, Inc., Chicago, IL) was used to conduct statistical multiple nonlinear regression analysis. Multiplicative power-law relationships were used to model effluent water quality as a function of design, operational, and influent water quality conditions. Seven parameters (six parameters for turbidity and head loss models) were used to initiate the regression process. The statistical significance of each parameter was evaluated based on the p-value (the smallest choice of α that would allow the null hypothesis to be rejected, where the null hypothesis is that the prediction is different from actual observation) obtained from the analysis. Specifically, the parameter with the highest p-value was eliminated if its p-value is larger than 0.05. The regression was redone with the remaining parameters. The process was repeated until all p-values of the remaining parameters were less than 0.05.

Based on a preliminary investigation, seven independent parameters (six parameters for the turbidity and head loss model) were chosen for model regression. They are filter depth, media size, filtration rate, turbidity, running time, temperature, and the influent concentrations of the variable to be predicted (turbidity, zooplankton, or phytoplankton).

A total of 135 data points were collected and used in statistical analysis (three filters × nine runs × five sampling events per run per filter). Based on statistical requirements, 95 data points (about 70% of the total data points) were randomly chosen to develop the regression models and the other 40 data points were used to validate the models.

RESULTS AND DISCUSSION

Filtration performance

The working conditions of the crumb rubber filters are summarized in Table 1. According to the results, maximum turbidity removal efficiency was 71%, and the average removal efficiency was about 35%. For phytoplankton, up to 75% was removed with an average removal of 58%. For zooplankton, up to 78% zooplankton was removed with an average removal of 50%. Head loss varied from 4 to 315 cm after an 8-h run, depending on the operational conditions. The overall efficiencies were calculated based on the average values of influent and effluent concentrations, while the maximum efficiencies were based on the field influent and effluent concentrations measured simultaneously.

Table 1. Ranges of turbidity and planktons in the lake water.

Parameters	*Turbidity*	*Phytoplankton*	*Zooplankton*	*Head loss*
Units	NTU inf./eff.	#/mL inf./eff.	#/L inf./eff.	cm
High	24.8/11.8	5307/1987	230/180	315
Low	8.27/4.26	1040/387	30/10	4

inf., influent concentration; eff., effluent concentration.

Suspended matter removal efficiencies under various design and operational conditions are presented in Table 2. To provide an overview of various factors on filter performance, each value is expressed as the average value ± standard deviation for five sampling events during the 8-h run described previously. These results indicate that reducing crumb rubber media size enhanced suspended matter removal. Reducing filtration rate also enhanced filtration performance with a few exceptional data points. The lower removal efficiency of zooplankton (>50 μm) compared to phytoplankton (10–50 μm) may be a function of zooplankton motility in water, which may allow for zooplankton penetration into the filter media. The effect of filter depth on suspended matter removal was not clear from Table 2. It should be noted that other parameters (temperature, water quality, etc.) also varied during data collection, and the influence of the variations are not apparent. Because these average data are a function of several independent variables, a statistical analysis with individual data points was used to reveal the individual effect of each factor.

Statistical modeling

Several regression approaches (linear, power function, etc.) were tried, and multiplicative power-law relationships gave the best results. This was expected because the power law function is a general approach and used widely in statistical regressions. Therefore, the multiplicative power-law relationships were assumed to describe the effluent water quality as a function of design, operational, and influent water-quality conditions. Using this approach, four models were developed to predict effluent turbidity, phytoplankton concentration, zooplankton concentration, and head loss, respectively. The *p*-values of the factors, for each of the models presented below, are presented in Table 3.

a) $\text{Turbidity} = 2.26 \times \text{Media Size}^{0.23} \times \text{Temperature}^{-0.04} \times \text{Turbidity}_{\text{inf}}{}^{0.49}$
b) $\text{Phytoplankton} = 2.06 \times \text{Filtration Rate}^{0.21} \times \text{Media Size}^{0.30} \times \text{Phytoplankton}_{\text{inf}}{}^{0.69}$

Table 2. Suspended solid removal under various design and operational conditions.

Target matter	*Filter depth meters*	*Filtration rate* $m^3/h \bullet m^2$	*Removal efficiency %*		
			0.66 mm media	*1.2 mm media*	*1.9 mm media*
Turbidity	0.6	24.4	42 ± 4	39 ± 5	27 ± 6
		48.9	33 ± 6	27 ± 7	22 ± 8
		73.3	37 ± 12	33 ± 4	24 ± 7
	0.9	24.4	44 ± 15	40 ± 14	30 ± 13
		48.9	44 ± 3	38 ± 2	31 ± 3
		73.3	36 ± 3	28 ± 4	21 ± 2
	1.2	24.4	48 ± 6	37 ± 8	29 ± 9
		48.9	40 ± 3	32 ± 3	25 ± 3
		73.3	38 ± 3	31 ± 3	23 ± 6
Phytoplankton	0.6	24.4	58 ± 10	58 ± 8	50 ± 7
		48.9	50 ± 3	40 ± 5	34 ± 3
		73.3	46 ± 5	42 ± 7	31 ± 9
	0.9	24.4	69 ± 4	63 ± 5	58 ± 3
		48.9	70 ± 3	62 ± 3	59 ± 6
		73.3	62 ± 4	54 ± 3	50 ± 6
	1.2	24.4	71 ± 3	68 ± 3	61 ± 5
		48.9	63 ± 2	56 ± 4	52 ± 7
		73.3	62 ± 3	57 ± 3	49 ± 8
Zooplankton	0.6	24.4	59 ± 12	56 ± 19	34 ± 9
		48.9	66 ± 5	60 ± 7	40 ± 5
		73.3	61 ± 6	51 ± 6	35 ± 9
	0.9	24.4	66 ± 8	56 ± 5	35 ± 9
		48.9	60 ± 4	49 ± 11	30 ± 15
		73.3	63 ± 8	44 ± 14	30 ± 14
	1.2	24.4	64 ± 2	44 ± 2	38 ± 19
		48.9	63 ± 6	45 ± 11	31 ± 7
		73.3	63 ± 3	55 ± 10	33 ± 14

Table 3. *p*-Values for each factors included in regression models.

	p-*values*			
Parameters	*Turbidity model*	*Phytoplankton model*	*Zooplankton model*	*Head loss model*
Media size	<0.0001	<0.0001	<0.0001	<0.0001
Filter depth	×	×	×	<0.0001
Filtration rate	×	<0.0001	×	<0.0001
Turbidity	<0.0001	×	×	0.026
Temperature	0.0101	×	×	<0.0001
Running time	×	×	×	<0.0001
Phytoplankton	×	<0.0001	×	×
Zooplankton	×	×	<0.0001	×

c) Zooplankton $= 0.67 \times$ Media Size$^{0.63} \times$ Zooplankton$_{inf}{}^{0.91}$
d) Head Loss $= 0.19 \times$ Filter Depth$^{0.74} \times$ Filtration Rate$^{1.34} \times$ Time$^{0.21} \times$ Turbidity$_{inf}{}^{0.21} \times$ Temperature$^{-0.14} \times$ Media Size$^{-1.27}$

- Inf: influent
- Media Size as effective size: mm
- Filter depth: meter
- Filtration rate: $m^3/h{\cdot}m^2$
- Turbidity: NTU
- Temperature: °C
- Phytoplankton: # organisms/mL
- Zooplankton: # organism/L
- Head loss: cm

The *p*-values indicate that the factors included in these models are correlated with the effluent water quality and head loss. The value of the constant related to each factor shows the importance of that factor. As shown in the model, media size has a substantial effect on all of the dependent variables. Increasing media size increased effluent turbidity, effluent phytoplankton concentration, and effluent zooplankton concentration and reduced head loss, as discussed under filtration performance. Increasing filtration rate increased the effluent concentrations of phytoplankton and head loss, but had a limited impact on turbidity and zooplankton removal. Given the filter depths used in this study, there was no correlation between filter depth and the removal of suspended matters.

Verification of regression models

Regression models were validated using the 40 remaining data points (except the 95 data points used for model development), to predict effluent concentrations and head loss. The predicted values were compared with the actual data observed in field study. Field data vs. model predictions are presented in Figs. 1–4.

Filter effluent turbidity observed from the field study and those calculated from the model are compared in Fig. 1. Because all 40 data points are distributed closely around the dashed line (which has a slope of 1) the model prediction are congruent with the effluent turbidity data. The biggest deviations of the model prediction were 20% overestimation and 12% underestimation. Similar results were obtained for effluent phytoplankton, zooplankton, and head loss, as shown in Figs. 2 to 4. The R^2 values for the regression model calibration (based on the 95 data points) and the R^2 values for model validation (based on the remaining 40 data points) are presented in Table 4. Because the head loss R^2 values are close to 1.00 and all other R^2 values are higher than 0.8., it is presumed that the regression approach is a suitable tool for evaluating

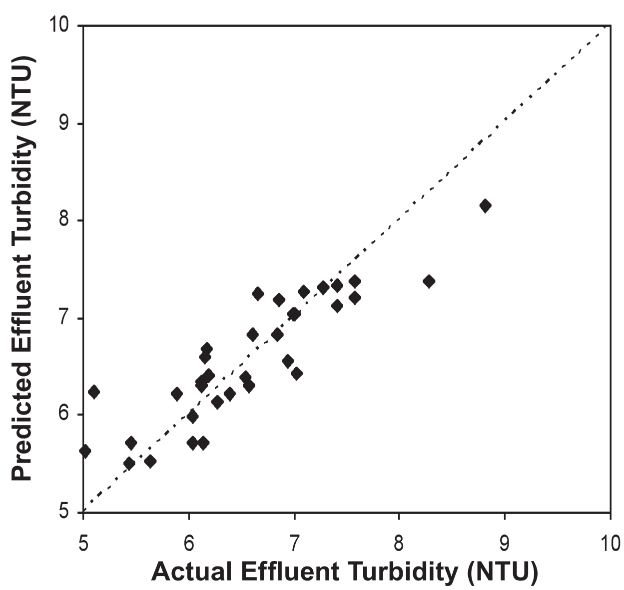

Figure 1. Turbidity regression model verification: actual effluent turbidity vs. model predictions.

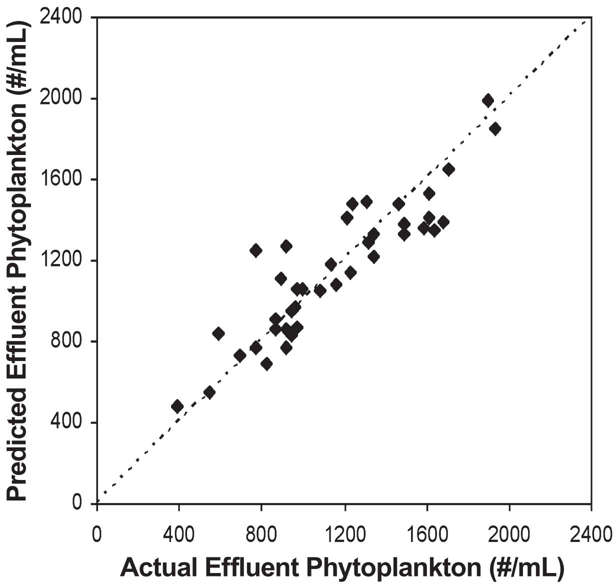

Figure 2. Phytoplankton regression model verification: actual effluent phytoplankton concentrations vs. model predictions.

the impacts of various factors on the performance of crumb rubber filtration.

Sensitivity analysis of various factors

To further evaluate the significance of various factors on filtration performance, sensitivity analyses were conducted. Maximum and minimum values of each factor were used as input to the regression model for prediction, while the other factors were held constant. The designed range of each factor, presented in Table 5, was based on the extremes of each factor encountered in the study. The predictions based on the maximum and minimum conditions of one factor were compared and the results are also shown in Table 5.

In Table 5, $*P._{Max}$ presents the predicted value using the maximum value of a factor and $*P._{Min}$ presents the predicted value using the minimum value. The $*P._{Max}/*P._{Min}$ ratio indicates the significance of the factor's influence on model predictions. A ratio of $*P._{Max}$ to $*P._{Min}$ around 1.0 indicates that the factor does not affect the filter performance criterion according to the model (e.g., effluent turbidity, effluent phytoplankton concentration, effluent zooplankton concentration, or head loss). The symbol "×" means this factor was not included in the regression model because it did not have a significant impact on filtration performance according to the statistical analysis. In reality, these factors may have had some effect on performance, but those effects were not significant enough to merit inclusion in the regression model. As shown in Table 5, media size, temperature, and influent turbidity impact turbidity removal. Increasing media size 0.66 to 1.9 mm, temperature from 1 to 30°C, and influent turbidity from 5 to 20 NTU increased the effluent turbidity by 27, −12, and 97%, respectively. Changing filtration rate from 24.4 to 73.3 m^3/hour·m^2 and filter depth from 0.6 to 1.2 m had no effect on effluent turbidity. Both filtration rate and filter media size affected effluent phytoplankton concentration. Effluent zooplankton concentration was only affected by filter media size. Head loss predictions were influenced by all factors, including filtration rate, media depth, media size, temperature, and influent turbidity.

The effects of crumb rubber size and filtration rate on filter performance are comparable to what would be predicted by classic interception [Equation (1)] and sedimentation [Equation (2)] models, respectively (Cleasby and Logsdon, 1999).

$$\text{Removal efficiency} = \frac{3}{2}\left(\frac{\text{Particle diameter}}{\text{Media diameter}}\right)^2 \quad (1)$$

Removal efficiency

$$= \frac{(\rho_p - \rho_w) \times g \times (\text{particle diameter})^2}{18 \times \mu \times \text{filtration rate}} \quad (2)$$

where g is the acceleration of gravity, ρ_s is the mass density of suspended matter, ρ_w is the mass density of water, and μ is the dynamic viscosity of water.

Increasing crumb rubber size or filtration rate lowered the crumb rubber filtration efficiency. However, the ef-

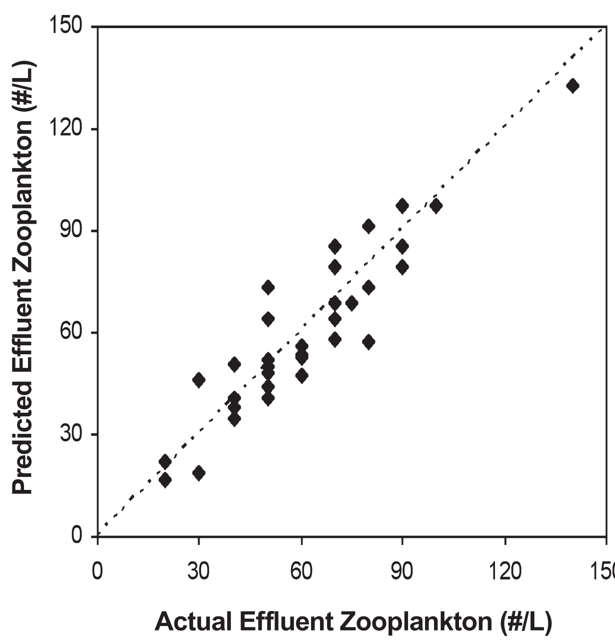

Figure 3. Zooplankton regression model verification: actual effluent zooplankton concentrations vs. model predictions.

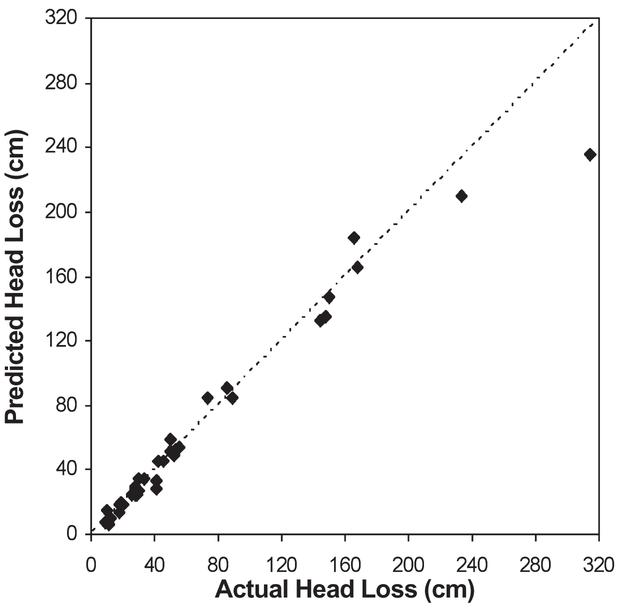

Figure 4. Head loss regression model verification: actual head loss vs. model.

fect of suspended matter size on filtration performance is incongruent with what would be predicted by these two models. Both models indicate better removal efficiency for particles with a larger diameter. However, our study gave a poorer removal for larger zooplankton than smaller phytoplankton. The poorer removal of zooplankton than phytoplankton may be due to the motility of zooplankton. Head loss in clean granular media filters can predicted with the Kozeny equation (Cleasby and Logsdon, 1999):

$$\text{Head loss} = \frac{k\mu}{\rho g}\,\frac{(1-\varepsilon)^2}{\varepsilon^3}\left(\frac{6}{d_{\mathrm{eq}}\psi}\right)^2 \times \text{filtration rate} \times \text{filter depth} \quad (3)$$

where g is the acceleration of gravity, d_{eq} is the grain diameter of a sphere of equal volume, ψ is the sphericity, μ is the absolute viscosity of fluid, ρ is the mass density of fluid, and k is the dimensionless Kozeny constant.

Although the regression head loss model developed herein partially resembles the Kozeny equation, head loss predictions with the Kozeny equation (data not shown) failed to adequately model head loss in the crumb rubber filter, even with a clean bed (Fig. 5). This was expected, because the crumb rubber elasticity and compressibility can lead to reduced pore size during filtration and a subsequent increase in head loss. This deviation from the classic filtration theory is reflected in the statistical model. For example, the exponent of 1.34 on filtration rate in the statistical model is greater than the exponent for filtration rate in the Kozeny equation. In addition, the exponent of 0.74 for media depth in the statistical model is less than the exponent for media depth in the Kozeny equation. The variations in these exponents are noteworthy because filtration rate and media depth can have a substantial influence on head loss in filters (Cleasby and Logsdon, 1999).

The Kozeny equation predictions, the regression model predictions and the actual head losses (run time of 0.5 h) are presented in Fig. 5 as a function of various filter depths and flow rates for media size 0.66 cm. At the filter run time of 0.5 h, the filter beds were treated as clean beds because the real clean bed headloss was not measured. Because the surface area and sphericity of the crumb rubber filter media is not known, typical sphericities for anthracite coal (0.53) and granular activated carbon (0.75) (Cleasby and Logsdon, 1999) were used in the Kozeny equation as a first approximation. It is clear that the regression model predictions are closest to the field observations, while the Kozeny equation predictions are deviated from the field observations, especially in high flow rate range. The distribution of the regression model prediction data in the 3D figure is similar to that of actual head loss data, while the Kozeny equation prediction data showed a different trend. The statistical model has an additional advantage of being able to predict increased head loss resulting from the removal of particles from the ballast water or for dirty filters.

Based on these results, design of a crumb rubber filter with good performance would benefit from smaller media size and lower filtration rate. However, the influence of media size on head loss and subsequent allowable filtration rate should be considered. Among the three sizes used in this study, a media size of 1.2 mm is recommended, since it resulted in good removal and low head loss. In this case, a filtration rate 73.3 m^3/hour·m^2 or higher (30 gpm/ft^2) can be achieved for more than 8 h to satisfy the requirement of fast ballasting. Temperature and water quality conditions also impact filtration performance, and should be considered for filter design.

Table 4. R^2 comparison of statistical model regression and verification.

Model	*Regression* R^2	*Verification* R^2
Turbidity model	0.81	0.86
Phytoplankton model	0.92	0.81
Zooplankton model	0.81	0.82
Head loss model	0.98	0.97

Table 5. Significance comparisons of the impacts of various factors on filtration performance based on regression models.

Affecting factor	*Factors units*	*Filtration rate* $m^3/h \cdot m^2$	*Filter depth meters*	*Media size mm*	*Temperature* °*C*	*turbidity*$_{inf}$ *NTU*
Factor range	Maximum	73.3	1.2	1.9	30	20
	Minimum	24.4	0.6	0.66	1	5
Ratio $*P._{Max}/*P._{Min}$	Turbidity model	×	×	1.27	0.88	1.97
	Phytoplankton model	1.26	×	1.37	×	×
	Zooplankton model	×	×	1.94	×	×
	Head loss model	4.31	1.67	0.26	0.61	1.34

Inf: influent.

CONCLUSIONS

The conclusions from this study are:

- Media size was the most significant factor affecting the treatment of ballast water using crumb rubber filtration: a smaller media size favored the removal efficiencies of all suspended matters (turbidity, phytoplankton, and zooplankton), but it resulted in a higher head loss.
- Filtration rate impacted phytoplankton removal and head loss: increasing filtration rate reduced the phytoplankton removal efficiency to some degree, and increased head loss notably.
- A deeper filter depth resulted in a higher head loss, but it did not benefit turbidity and plankton removal.
- Regression analysis indicated that effluent concentrations of phytoplankton, zooplankton, and turbidity were affected by their influent levels and crumb rubber media size. Water temperature and filtration rate also affected turbidity and phytoplankton levels, respectively. Filter depth, filtration rate, filtration time, turbidity, temperature, and media size all affected head loss development inside crumb rubber filters.
- Regression models developed under this study can be used to predict the effluent turbidity, phytoplankton, and zooplankton levels and head loss in-

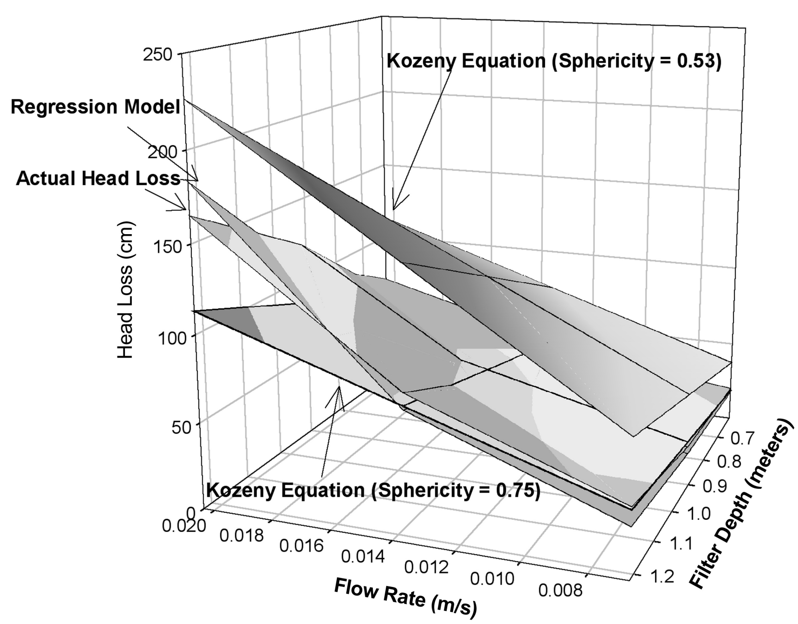

Figure 5. Comparison of regression model with Kozeny equation (media size = 0.66 cm).

side the crumb rubber filters. These models could be used to choose proper crumb rubber media size, filter depth, and filtration rate for ballast water treatment.

- Without modification the theories and models for conventional granular media filtration cannot be used to describe crumb rubber filtration. This may be due to the nature of the straining process, compressibility of crumb rubber media, size of plankton, and motility of zooplankton.

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