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Effect of average flow and capacity utilization on effluent water quality from US municipal wastewater treatment facilities

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ABSTRACT

There is increasing interest in decentralization of wastewater collection and treatment systems. However, there have been no systematic studies of the performance of small treatment facilities compared with larger plants. A statistical analysis of 4 years of discharge monthly report (DMR) data from 210 operating wastewater treatment facilities was conducted to determine the effect of average flow rate and capacity utilization on effluent biochemical oxygen demand (BOD), total suspended solids (TSS), ammonia, and fecal coliforms relative to permitted values. Relationships were quantified using generalized linear models (GLMs). Small facilities (40 m^3/d) had violation rates greater than 10 times that of the largest facilities (400,000 m^3/d) for BOD, TSS, and ammonia. For facilities with average flows less than 40,000 m^3/d, increasing capacity utilization was correlated with increased effluent levels of BOD and TSS. Larger facilities tended to operate at flows closer to their design capacity while maintaining treatment suggesting greater efficiency.

1. Introduction

Centralized wastewater collection, treatment, and disposal in the US began during the latter 19th Century with an effort to protect public health in cities and to mitigate nuisance conditions brought about through lack of local disposal sites for residential waste. In addition, the availability of piped water and flush toilets enabled "wet" collection and transport of wastes. High population density in large urban centers limited land available for disposal of the untreated waste, prompting construction of sewers. Between 1850 and 1920, the number of cities with more than 50,000 people increased from just under 400 to over 2700, and the population served by combined or sanitary sewers increased from 1 million to 25 million (Burian et al., 2000). The 1972 Federal Water Pollution Control Act (FWPCA) amendments to the Clean Water Act brought sweeping changes to wastewater treatment with a discharge permit system to protect surface water quality as its foundation. Approximately $80 billion in Federal investments through the construction grants program resulted in the construction of centralized secondary treatment plants, using the sewer infrastructure that had been built over the previous 75 years. In addition to economies of scale, the costs of compliance with National Pollutant Discharge Elimination System (NPDES) permits including treatment to higher levels and extensive monitoring may have favored larger facilities supported by fees from residential, commercial and industrial users.

Decentralized systems were dominated by on-site treatment in low density rural areas (U.S. Environmental Protection

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Agency [USEPA], 1997), but recent growth of suburban and exurban areas has increased use of on-site systems in these medium density developments. Data from the 2000 US Census indicated that one-third of new homes and the majority of mobile homes are served by on-site systems (USEPA, 2002). However, on-site systems are unable to meet common discharge standards for nitrogen met by centralized systems, and as a result are major contributors of nitrogen to the aquatic environment (Oakley et al., 2010). The need to serve communities too dense for on-site systems but far from existing sewers and centralized treatment facilities and location of communities near nitrogen sensitive watersheds has brought new interest in smaller collection systems served by satellite wastewater treatment plants. Factors such as the cost of building out collection systems and pumping wastewater, improvements in small system technology, and automated operation have led organizations such as National Decentralized Wastewater Resources Capacity Development to advocate for decentralized systems and small satellite plants (National Decentralized Water Resources Capacity Development Project, 2009).

Decreases in housing density affect the economies of scale derived from large centralized wastewater treatment through increased collection system costs (Carruthers and Ulfarsson, 2003). For smaller communities, the capital cost of conventional gravity sewers on average was found to be four times the cost of treatment with a similar relation for operation and maintenance costs. This is due to both the longer piping distances in lower density developments and the increased need for lift stations (WEF, 2008). Water reuse can also provide a significant incentive for smaller collection systems. In Denver, for example, pumping from a centralized facility constitutes 50% of the costs of reuse water (Good, 2006). Reducing the service area of a wastewater facility would reduce distribution system costs and energy consumption provided there were local opportunities for reuse.

The EPA has estimated that if current documented needs in the US are met there will be 1552 new treatment plants of which 53% will serve communities of fewer than 10,000 people or 4000 m^3/d wastewater flow (USEPA, 2008b). Many of these facilities are expected to replace failing on-site treatment systems. Total small community needs are $17 billion, 9% of the total wastewater monetary need (USEPA, 2008b).

There are regulatory issues that differentially impact small wastewater systems. One is significant fixed costs to apply for a discharge permit for a new or expanded plant. These fixed costs place a higher burden on smaller systems and thus are a disincentive to redesign and improve facilities. Small systems with significant dilution of their discharges may benefit from relaxed permit standards, particularly for constituents such as nitrogen. Furthermore increasingly limited resources for enforcement and focus on large dischargers may mean less regulatory attention paid to small facilities. Lack of oversight could result in fewer facility improvements or reduced effluent quality. Overall, the potential for proliferation of small wastewater treatment facilities coupled with constraints on monitoring and enforcement provides the rationale to investigate the effect of facility size on treatment performance.

Earlier statistical evaluations of treatment reliability were done in the 1970s in the midst of the Constructions Grants program. Effluent BOD and suspended solids (SS) data from 37 US treatment plants was characterized with lognormal distributions in order to develop a coefficient of reliability (COR), the probability of a plant achieving mean effluent quality at a selected fraction of the discharge standard. For any plant, prediction of the COR relied on knowing, or estimating, the coefficient of variance for BOD and SS (Niku et al., 1979). A comparison of treatment reliability as a function of process type was performed on 166 plants in Brazil which also used a lognormal distribution of effluent data and found that activated sludge processes achieved the highest reliability while septic tanks had the lowest, although plant capacity was not explicitly considered (Oliveira and Von Sperling, 2008). Oakley et al. (2010) found that on-site treatment systems were significantly less capable of meeting limits on watershed nitrogen loads than centralized biological nutrient removal (BNR) systems.

Linear regression analysis was used in a study of the effect of operations on individual treatment plant performance with the conclusion that no single or consistent group of factors, including flow, could explain individual plant variability in BOD and SS removal (Niku and Schroeder, 1981b). However, lack of identifiable factors affecting performance may have been partly due to the relatively narrow range of operating conditions at any individual plant. Niku and Schroeder (1981a) reported poor correlations between arithmetic mean annual flow and annual mean and standard deviation values for BOD and suspended solids in a sample of 43 activated sludge treatment plants ranging from 2000 to 800,000 m^3/d (0.56–209 mgd).

Overall, applicability of previous studies predicting the reliability of treatment plants is limited in that the methods require prior knowledge of the inherent mean and variance of effluent quality parameters for an individual facility or process type. As such, they do not provide a general basis for comparing the reliability of a network of decentralized treatment plants to a centralized system or the risk of excess contaminant loading to a watershed.

Mathematical optimization models have been developed to evaluate the effect of the degree of centralization, but the major objective function was cost with assumed economy of scale a major factor (Cunha et al., 2009; Wang and Jamieson, 2002; Voutchkov and Boulos, 1993). To address the need for predictive models of reliability, a statistical study was designed to test whether a relationship exists between average monthly flow, capacity utilization and effluent constituent levels and violation probability. The goal of the study is to provide guidance to planners, regulators, and utility managers in defining service areas and facility conditions which will provide economical treatment with reduced environmental risk.

1.1. *Generalized linear models*

Effluent concentration of a constituent and relative concentration, normalized to permit limits, will have both systematic variabilities, represented as its relationship to factors like facility size and capacity utilization, and random variability arising from changes in effluent water quality within a single facility over time and inherent differences between facilities including influent characteristics, facility age and process type. Factors which may be associated with plant size such as equipment, maintenance levels, labor quality and hours could lead to variation in treatment performance (Niku and Schroeder, 1981b).

Since the work of Niku et al., the generalized linear model (GLM) has been developed as a flexible statistical method of accurately modeling a wide variety of data including non-normal distributions and discrete variables. In a GLM, the response or the dependent variable Y can be assumed to be a realization from any distribution in the exponential family with a set of parameters (McCullagh and Nelder, 1989). Thus positively-skewed, nonnegative data such as effluent concentrations of constituents can be modeled with a gamma or lognormal distribution and violation probability can be directly modeled with a binomial distribution using the same statistical method. The GLM enables simultaneous consideration of more than one independent variable without the assumption of linear relationships between independent and dependent variables.

In GLM, a smooth and invertible link function transforms the conditional expectation of Y to a set of predictors.

$$G(E(Y)) = \eta = f(\mathbf{X}) + \epsilon = \mathbf{X}\beta^T + \epsilon \tag{1}$$

β^T is the transposed vector of model parameters, $\boldsymbol{X}$ is the set of predictors or independent variables, E(Y) is the expected value of the response variable, ϵ is the error, and G(.) is the link function. The ability to choose a distribution for Y and the associated link function allow GLM to model a wide variety of data. For skewed variables with a lower bound of 0 such as effluent concentrations and relative concentrations, the gamma distribution with the inverse link function is appropriate; for binary variables such as modeling probability of violations, the binomial distribution with the logit link function is appropriate; for discrete variables such as number of violations over a given period the Poisson distribution is appropriate. If a normal distribution is assumed with an identify link function it collapses to a linear model – see McCullagh and Nelder (1989) for information about other distributions and link functions.

After choosing a distribution and link function, the model parameters are estimated using an iterated weighted least squares (IWLS) method that maximizes the likelihood function as opposed to an ordinary least squares method used in linear modeling. The best model is chosen based on the Akaike Information Criteria (AIC, Akaike, 1974) by comparing models fit using all possible subsets of predictors. For each model, the AIC is computed as:

$$AIC = 2k - 2L \tag{2}$$

where L is the logarithm of the likelihood function of the model with the predictor subset under consideration obtained from the IWLS procedure mentioned above and k is the number of parameters to be estimated in this model. The model with the lowest AIC is taken to be the 'best model'. Models can also be tested for significance against a null model or an appropriate subset model using a chi-squared test.

2. Methods

To analyze the effect of treatment facility size and capacity utilization on effluent quality and violation history, data from the Environmental Protection Agency's Integrated Compliance Information System (ICIS) was used. ICIS contains enforcement and compliance information for over 10,000 wastewater facilities with NPDES permits in 28 states and US territories (USEPA, 2008a). The ICIS database is gradually replacing the older Permit Compliance System (PCS); hence it does not have data for facilities in the 22 states that have not yet switched their reporting to the newer system. For those states with data, however, the most recent 2–5 years of discharge monthly reports (DMR) are available for most facilities. The data include all required reporting for each facility, including effluent concentrations for permitted constituents, influent measurements, flow through the plant, and the permitted discharge limits each month.

To reduce data processing time and storage requirements, a systematic sample consisting of 5% of the ICIS database, (629 facilities) was used for analysis. The data set was further reduced by filtering out facilities with insufficient data for analysis of each of the four constituents, BOD, TSS, ammonia, and fecal coliforms, resulting in four separate data sets. The data set for BOD contains 209 facilities, TSS has 211, ammonia has 110, and fecal coliforms has 109 with an average of 41 months of data per facility.

2.1. *Prediction of effluent constituent levels*

An important criterion related to treatment performance is effluent concentration, but permit standards vary considerably between plants due to factors such as receiving water quality, dilution factor, location, and season. Plants may be designed to meet current permit levels or anticipated future permit levels. As a result of these local differences, the absolute concentration of a constituent in the effluent is expected to differ between treatment facilities of equivalent treatment performance and reliability. To account for this the relative concentration was selected to be the dependent variable for regression, where relative concentration is the reported average monthly discharge concentration for a given constituent divided by the discharge permit standard.

Relative concentration is greater than zero and positively-skewed so the gamma function and its associated canonical link function, the inverse, was selected for GLM modeling of effluent constituent levels resulting in the following equation.

$$\frac{1}{E(R)} = \boldsymbol{X}\beta^T + \epsilon \tag{3}$$

where $E(R) > 0$ is the predicted effluent concentration of the constituent (BOD, TSS, ammonia or fecal coliforms), $\boldsymbol{X}$ is the matrix of independent variables, ϵ is the error, and β^T is the transposed vector of model parameters which are estimated following the methods described above.

To determine the effect of facility size on treatment performance two independent variables have been chosen. First is the logarithm of the average monthly flow rate, *A*. Flow rates of facilities in the data sets vary from 1 to 335,000 m^3/d. It was hypothesized that plant performance could also be influenced by over- or under-loading, so the second independent variable is capacity utilization, C, defined as the reported monthly average flow rate divided by the design flow rate. The product of these two variables, AC, is also included as an independent variable, and all combinations of independent variables are compared using AIC. Process type was explicitly ignored as an independent variable due to lack of data and a desire to quantify performance explicitly as related to decentralization. Analysis was performed using R, a free software package for statistical computing and graphics.

2.2. *Probability of violation*

To quantify risk the frequency and magnitude of permit violations were modeled. Permit standards are based on scientific water quality criteria adopted to protect aquatic life and other uses of receiving waters, and therefore the probability of violations are a reasonable indicator of risk of significant adverse effects to the receiving water. The probability of a violation also can be considered a second indicator of treatment plant reliability. Permit violations subject the plant owner/operator to regulatory penalties, including fines.

To model violation frequency the response variable, effluent concentration, was converted to a binomial variable where 1 represented a permit violation and 0 represented no violation. The GLM is fitted using a binomial distribution with the logit link function as follows:

$$\ln\left(\frac{E(V)}{1-E(V)}\right) = \mathbf{X}\beta^{T} + \epsilon \tag{4}$$

where $E(V)$ is the probability of a violation that ranges between 0 and 1, and other terms are as described for equation (3). With the fitted best model the risk of violations can be estimated.

2.3. *Violation magnitude*

A second component of risk is the magnitude of violations. Large exceedances of discharge standards could have a significant effect on receiving water quality, especially in cases where there is little dilution, sensitive aquatic habitat, or proximate human use. The relative discharge values exceeding the threshold are obtained from the data and best GLM model based on the three independent variables is fitted using the gamma distribution and the inverse link function using the same procedure described in section 2.1.

3. Resuts and discussion

Results of GLM analysis for prediction of effluent BOD as a function of plant flow and capacity utilization are presented in detail. Since the same procedure was followed for TSS, ammonia and fecal coliforms, results for these constituents have been summarized to allow discussion of differences in effluent trends among the four constituents.

3.1. *Effluent concentration model – BOD*

Flow rates of the 209 facilities used for BOD analysis ranged from 1 m^3/d (0.001 MGD) to 335,000 m^3/d (100 MGD) and capacity utilization rates ranged from 5% to 180%. Interestingly, 13% of those facilities average flow rates above their permitted capacity. Because EPA regulations require a plant to begin the redesign phase when a facility averages more than 85% of its design capacity, these facilities are in violation of that portion of their permit. Exceeding the hydraulic capacity of plants turns out to be a significant factor in effluent quality for smaller plants, as will be discussed below.

Using these 209 facilities, GLMs to predict relative BOD concentration were fit for all possible combinations of the independent variables (logarithm of average flow and capacity utilization), as described in section 2.1. The AIC values of each model were compared, as shown in Table 1, and Cond_{A+C+AC} was identified as the best model. This model uses both independent variables as well as the nonlinear product and was significantly better at fitting effluent data than the unconditional model and Cond_{A} and Cond_{A+C} at alpha = 0.05. This model is used for subsequent analysis.

A generalized linear model from the gamma family was fit to the data using the inverse link function. Thus, the expected value of the relative effluent BOD, $E(R)$, is modeled as:

$$1/E(R_{\mathrm{BOD}}) = 3.03 + 0.0691A + -0.308C + 0.176AC \tag{5}$$

As shown in (5), positive coefficients indicate a negative correlation between the independent variable and response variable so large and highly utilized facilities have lower expected effluent BOD than small facilities operating close to

Table 1 – GLM functions, parameters, β^T, and associated AIC values for prediction of relative effluent BOD. R = predicted monthly average BOD (mg/l); A = log (average monthly flow) m^3/d; C = fraction of hydraulic capacity utilized; se = standard error.

	Uncond	Cond_{A}	Cond_{C}	Cond_{AC}	Cond_{A+C}	Cond_{A+AC}	Cond_{C+AC}	Cond_{A+C+AC}
1/R=	β_0	$\beta_0+\beta_1A$	$\beta_0+\beta_2C$	$\beta_0+\beta_3AC$	$\beta_0+\beta_1A+\beta_2C$	$\beta_0+\beta_1A+\beta_3AC$	$\beta_0+\beta_2C+\beta_3AC$	$\beta_0+\beta_1A+\beta_2C+\beta_3AC$
β_0 (se)	2.62 (0.0332)	2.79 (0.0405)	2.83 (0.0714)	2.79 (0.0377)	3.26 (0.0829)	2.79 (0.0406)	2.89 (0.0678)	3.03 (0.0989)
β_1 (se)	–	0.143 (0.0160)	–	–	0.182 (0.0177)	0.00744 (0.0254)[a]	–	0.0691 (0.0343)
β_2 (se)	–	–	−0.299 (0.0869)	–	−0.588 (0.0870)	–	−0.155 (0.0849)[a]	−0.308 (0.114)
β_3 (se)	–	–	–	0.266 (0.0217)	–	0.259 (0.0332)	0.254 (0.0222)	0.176 (0.0450)
AIC	−3	−175	−26	−290	−269	−288	−295	−302

a Term not significant at $\alpha = 0.05$.

or over their permitted capacity, as shown in Fig. 1. More specifically, small facilities (40 m^3/d) are predicted to discharge BOD that averages 40% or more of permit limits while predicted effluent BOD from large facilities (400,000 m^3/d) is consistently 33% of permit limits. Furthermore, for facilities 40,000 m^3/d and larger, capacity utilization has almost no effect on the effluent BOD while for smaller facilities increasing capacity utilization is associated with increasing relative effluent BOD.

3.1.1. *Comparison of model and actual data*

A boxplot shows actual effluent data sorted by facility flow rate (Fig. 2). The whiskers of the boxplot indicate the 5th and 95th percentiles, and not the interquartile range (IQR) times 1.5 as is common for boxplots, and the black squares show the predicted effluent level for the average flow rate and capacity utilization in that size range. The predicted values consistently fall between the first and third quartiles and also follow the trend shown in the median values up to 40,000 m^3/d, specifically that there is a decrease in average BOD discharged as plants increase in size. Above 40,000 m^3/d, however, there is a significant increase in median effluent BOD not predicted by the model.

Both the IQR and the whisker length decrease as facilities get larger, and it is especially notable that the 95th percentile effluent BOD is above the permit limit for the two smallest size categories. By contrast, the largest facilities have the highest median discharge but the 95th percentile is furthest below the permit limit, showing that median discharge is not related to permit violations in the same way for larger facilities as it is for smaller plants. The latter result suggests that large facilities discharge closer to their permit limits on average but also have fewer violations, possibly due to more consistent treatment.

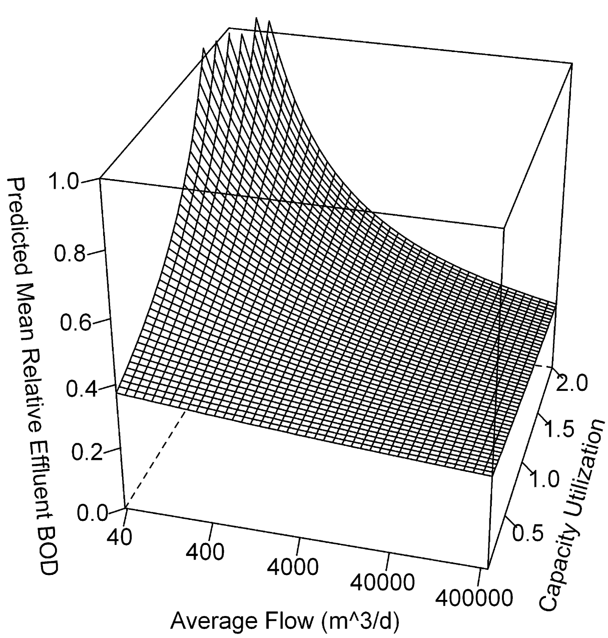

Fig. 1 – Predicted relative effluent BOD concentration versus average flow and capacity utilization.

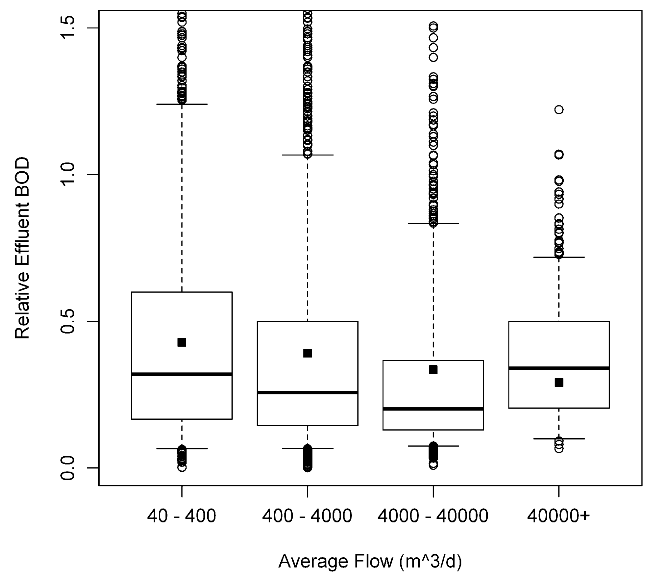

Fig. 2 – Boxplot showing variation of BOD discharges by facility size where whiskers show 5% and 95% percentiles and black square is the model prediction using the average flow and capacity utilization for facilities in the size range.

The large variation in BOD discharges, both for facilities of a given size range as shown but also within individual facilities, indicates that flow and capacity utilization are not sufficient to predict a facility's performance in any given month; however, for comparison of the BOD removal among the entire data set or prediction for a single facility over a long period of time, the GLM does provide a good estimate of effluent BOD.

3.2. *BOD permit limit violations*

While average effluent levels provide one measure of treatment performance, permit violations may be a better measure of the risk of significant BOD release to receiving waters. As Fig. 2 shows, though the largest facilities have the highest median relative effluent BOD they have the fewest discharges above their permitted values. To directly model probability of permit violations the data for effluent BOD are transformed into a 1 for effluent BOD exceeding the permit limit – a violation, or a 0 indicating no violation. As described in section 2.2, a binomial GLM was fit to the data using the logit link function. The model with the best set of predictors (lowest AIC) is:

$$\ln\left(\frac{E(V_{BOD})}{1-E(V_{BOD})}\right) = -3.35 + -0.128A + -0.284AC \qquad (6)$$

The negative coefficients indicate a negative correlation for average flow and for the combined term, meaning larger facilities and more highly utilized facilities have lower violation rates as shown in Fig. 3.

Consistent with the average effluent BOD data, as facility size increases the predicted fraction of months in violation decreased, with small facilities (40 m^3/d) violating their BOD permits in more than 6.6% of months while large facilities (400,000 m^3/d) violate BOD limits less than 2.2% of the time.

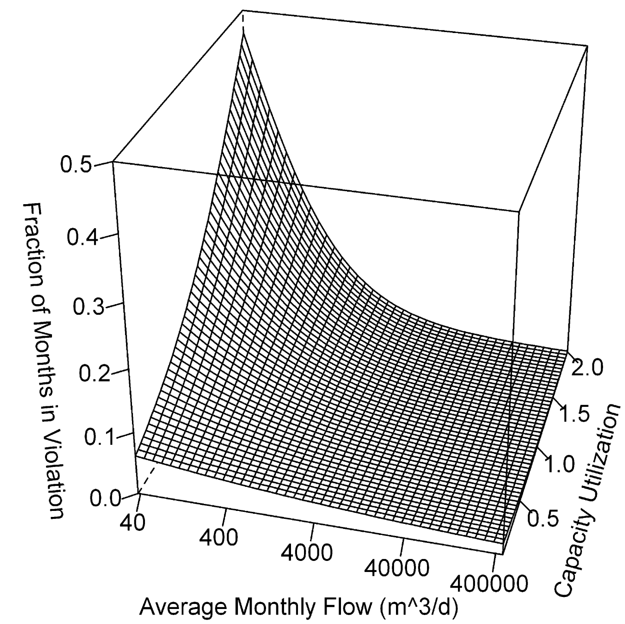

Fig. 3 – Model prediction of BOD violations versus average flow and capacity utilization.

Second, capacity utilization has a large positive relationship with violation frequency for facilities 4000 m^3/d and smaller, while for large facilities capacity utilization has almost no relationship to violation frequency.

3.2.1. *Comparison of model and actual violation data*

Actual violation data are grouped by plant size and shown in a boxplot (Fig. 4) of the fraction of months in violation. As before, the whiskers indicate the 5th and 95th percentiles.

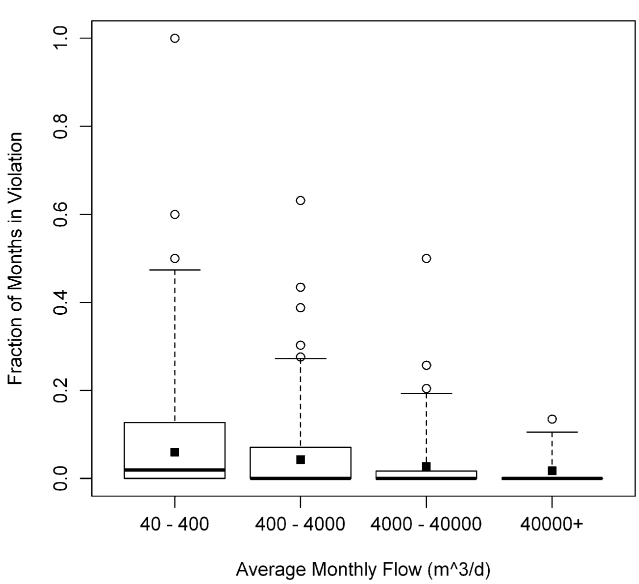

Fig. 4 – Boxplot showing variation of violation fractions grouped by facility size where whiskers show 5% and 95% percentiles of BOD violation frequency and square is the model prediction calculated using the average flow and capacity utilization for facilities in the size range.

The lower whisker and first quartile fall at zero violations for all facility size ranges, and even the median is zero for all except the smallest size range indicating most of the facilities had zero violations in the database and are performing reliably. The upper whisker and third quartile do show trends among the worst 5% and 25% of facilities, however. The model predictions and actual data show that increasing facility size is associated with fewer BOD violations. The worst 5% of plants smaller than 400 m^3/d violate their BOD permit limits nearly half of the time, while the worst 5% of plants larger than 40,000 m^3/d have violations only 11% of the time. Additionally, for the smallest facilities one-quarter violated limits at least 12% of months, or 1.4 BOD violations per year. While most facilities are reliable and have no violations, significantly more small plants violate their BOD permits more frequently than larger ones and the GLM captures this trend.

3.3. *Violation magnitude and risk*

To model violation magnitude, the BOD data are filtered to include only those data points in which a violation occurred. Of the 209 facilities in the original data set, there were 454 violations at 84 unique facilities with flow rates from 4 m^3/d to 40,000 m^3/d. A comparison of models showed that neither average flow rate nor capacity utilization was significant with respect to violation magnitude. The intercept indicates that BOD limit violations for facilities of all sizes average 1.6 times the permitted value. While the mean violation magnitude is 1.6 times the permit, the median is only 1.3 and 95% of the violations are less than 2.8. 15% of violations are serious violations, defined as effluent discharges more than double the permitted value for BOD, and there are a small number of extreme violations up to 20 times the permit.

Risk is considered as the violation frequency multiplied by the relative magnitude, but because violation magnitude does not vary with facility flow rate or capacity utilization, risk is characterized by the violation frequency alone. Modeled violation probabilities translate to a violation every 8 months for the smallest facilities (40 m^3/d), every 2.5 years for the medium facilities (4000 m^3/d), and every 10 years at the largest facilities (400,000 m^3/d). Because 15% of these violations are serious, the expected return period for serious BOD permit violations is 4.3 years at small facilities, 16 years at medium-sized facilities, and 70 years at the largest. Wastewater treatment facilities are operated for many decades so it is likely that all but the largest facilities will have several serious BOD violations during its lifetime. This is especially true for smaller facilities.

3.4. *Predicted effluent TSS, ammonia, and fecal coliforms*

Using the same methods as presented previously for BOD, average relative effluent values for TSS, ammonia, and fecal coliforms were predicted using GLMs with the gamma distribution and inverse link function.

$$1/E(R_{TSS}) = 3.41 + 0.233A + -0.626C \tag{7}$$

$$1/\,E(R_{NH_4}) = 3.91 + 0.329A + -0.423AC \quad (8)$$

$$1/\,E(R_{FC}) = 7.28 \quad (9)$$

The best GLMs for each constituent differ somewhat: the product AC was not significant for TSS, and capacity utilization, C, was not significant for ammonia except as the product AC. However, both TSS and ammonia show similar trends as BOD. Specifically, small and highly utilized facilities are predicted to discharge higher average relative levels of these two constituents. None of the flow or capacity variables produced better prediction of fecal coliforms than the unconditional model. The difference is not surprising because disinfection is carried out in a separate process from the biological treatment processes that determine the effluent BOD, total suspended solids, and ammonia.

3.5. *Risk of TSS, NH_4, and FC permit violations*

Violation frequency and risk models for TSS, ammonia, and fecal coliforms using a binomial GLM are as follows:

$$\ln\left(\frac{E(V_{TSS})}{1 - E(V_{TSS})}\right) = -3.37 + -0.167A + -0.275AC \quad (10)$$

$$\ln\left(\frac{E(V_{NH_4})}{1 - E(V_{NH_4})}\right) = -3.95 + -0.483A + -0.658C \quad (11)$$

$$\ln\left(\frac{E(V_{FC})}{1 - E(V_{FC})}\right) = -4.30 + -0.212A \quad (12)$$

The coefficients for average flow are negative for all four constituents, meaning that larger facilities violate their permits less frequently than smaller facilities. This trend is especially strong for ammonia while BOD actually shows the weakest trend. Like for BOD, small and highly utilized facilities have higher rates of TSS violations; however under-utilized facilities are predicted to have more frequent ammonia violations than highly utilized ones. Interestingly the GLM for expected frequency of violations of fecal coliform standards is associated only with plant average flow, with higher risk at smaller plants.

Average flow rate is a statistically significant predictor in more of the best-fit models than capacity utilization. Therefore, model predictions of violation rate are presented in Table 2 with capacity utilization fixed at the observed mean value of 0.69 and three flow rates: 40, 4000, and 400,000 m^3/d. The smallest facilities (40 m^3/d) are estimated to violate BOD and TSS permits about 15 times more frequently than the largest facilities (400,000 m^3/d), ammonia permits 75 times more frequently, and fecal coliform permits 7 times more often. Because BOD and TSS are closely related in treatment processes, it is not surprising that the models of those two constituents have very similar violation rates and magnitudes. By contrast, there are fewer fecal coliform violations for facilities of all sizes, but the magnitude of violations is much greater relative to permits levels. While disinfection processes are more reliable generally, the failures that do happen appear to be more significant.

As a constituent of increasing concern (State-EPA Nutrient Innovations Task Group, 2009), the risk for ammonia violations stands out both for the predicted frequency of violations for small facilities as well as the severity of the violations. Modeled violation probabilities translate to a violation every 4.5 months for the smallest facilities (40 m^3/d) and every 2.8 years for the medium facilities (4000 m^3/d). 40% of these violations are double the permitted value, so the expected return period for serious ammonia permit violations is 11 months at small facilities and 7 years at medium facilities while larger facilities have significantly fewer violations. This finding indicates that care should be taken when implementing a decentralized wastewater infrastructure in watersheds sensitive to excess ammonia such as the Chesapeake Bay.

3.6. *Implications of results*

Small facilities often have fewer resources for upgrading or expansion of their treatment facilities which may be an explanation for the number of plants reporting flow rates over the design capacity that in turn affects performance. Many small wastewater facilities also may have fewer hours of attended operation than centralized plants. While large facilities can afford to have full time certified operators and engineers, small facilities can often only afford part-time contract operators. One possible result of limited oversight is that management is less responsive to process changes or upsets, resulting in increased effluent variability and a higher violation frequency. Coupled with the reduced regulatory oversight for small facilities, there is little incentive to improve their operation.

Table 2 – Summary of GLM-predicted violation rates and magnitudes based on average monthly flow rate with capacity utilization fixed at 0.69. Serious violations are those where the discharge concentration was twice the permit limit.

	BOD	TSS	NH_4	FC
Violation rate (40 m^3/d flow)	13%	15%	22%	3.5%
Violation rate (4000 m^3/d flow)	3.4%	3.3%	3.0%	1.3%
Violation rate (400,000 m^3/d flow)	0.8%	0.7%	0.3%	0.5%
Mean violation magnitude (effluent/permitted)	1.63	1.75	2.59	2.34
Serious violations (% of total violations)	15%	20%	40%	37%

4. Conclusion

Statistical evaluation of discharge monthly report (DMR) data for 211 wastewater treatment plants in the EPA ICIS-NPDES database using a generalized linear model (GLM) indicated significantly increased frequency of permit violations for BOD, TSS, ammonia, and fecal coliforms as plant capacity decreased. This trend was consistent over the entire range of plant capacities sampled: 1–335,000 m^3/d. For facilities smaller than 40,000 m^3/d, there is also a trend that increasing facility size correlates with decreasing effluent constituent concentrations relative to permitted values for BOD, TSS, and ammonia. The trend toward increasing risk of discharges for smaller facilities exceeding permit limits was strongest for ammonia. Facilities larger than 40,000 m^3/d have predicted effluent levels of constituents that are closer to permit limits but reduced violation rates, suggesting that larger plants can operate more efficiently than smaller facilities by not over-treating wastewater. For facilities smaller than 4000 m^3/d, exceeding the plant design hydraulic capacity was a significant factor in decreased treatment reliability. Small facilities near or over their design flow rates had significantly more permit violations and higher relative effluent levels for BOD, TSS, and ammonia than those operating under their hydraulic capacity.

The GLM approach developed in this research offers a flexible framework for modeling a suite of variables with different characteristics (skewed, binary, discrete etc.) unlike the more commonly used linear modeling methods. As demonstrated above, we obtained insights into reliability and risk associated with facility size which may guide effective management and planning of treatment plants.

If networks of decentralized small facilities are to become a larger part of the wastewater treatment infrastructure in the US, planners and regulators should consider the GLM results that suggest the possibility of increased aggregate risk to surface water quality and public health from multiple small plants.

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