Breakeven Costs of Distributed Advanced Technology Water Treatment Systems

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<u>Abstract</u>

The financial implications of using distributed versus centralized advanced water treatment technologies to address certain stringent water quality criteria are examined. Specifically, we estimate for a model water quality parameter the relative financial burdens required to address advanced water treatment requirements using centralized and distributed treatment approaches. The analytical approach applied can be generalized to optimize technology selection for any specific water quality parameter(s) of interest in a given water, e.g. desalination or water processing for re-use application.

The specific application of the model discussed here posits a water quality degradation inherent to the distribution network. This is a broad application of the model in that such degradation can be modeled either as "sharp" (e.g. immediate degradation upon discharge to the distribution network), or "progressive" (e.g. the leaching of pipe materials or formation of disinfection by-products (DBPs) in its spatial and temporal character. A relatively straightforward application of the model to desalination applications would be a scenario of "partial" centralized desalination combined with point of use/point of entry desalination for consumer use. The processing of grey water for reuse purposes usually requires treatment of relatively high dissolved organic carbon water, and requires considerable disinfectant residuals to ensure public safety. This paper thus addresses DBP formation within distribution systems as a water quality issue. In the paper we estimate disinfection by-product (DBP) formation within a distribution network, and then use this cost estimate to calculate "break-even" costs for alternative use of distributed water treatment technologies to meet DBP exposure limits . A basic linear DBP formation model is employed and hydraulic residence time distribution is calculated using EPA water distribution system survey data.

For an estimated maximum water age of approximately 21 days, and network DBP precursor concentrations ranging from 1 to 5 mg/L, our model indicated that the centralized treatment approach would need to reduce DPB precursors to approximately 0.076 mg/L. The optimum selection of technology improvements needed to provide this level of reduction were estimated for various system sizes and feed water quality levels, with optimal technology selection being found to vary as a function of economies of scale.

The break-even cost associated with equivalent efficiency distributed treatment systems was calculated by dividing the estimated cost of required central treatment facility upgrades by the number of residential connections receiving water having DBP concentrations in excess of regulatory limits. For our sample utility, we found a maximum estimated break-

even single connection cost of $US 25,000 dollars for systems serving between 101 to 500 people, and a minimum break-even single connection cost of $US 5,000 dollars for systems serving more than 500,000 people.

I. INTRODUCTION

This paper presents a financial analysis of the implementation of distributed technology systems to provide advanced treatment of water for direct human consumption. The degradation of water quality within a distribution network, a phenomenon that presents considerable financial and technical obstacles to the delivery of secure water supplies to end-point consumers, is one of several problematic issues that might well be addressed by distributed systems. The approach described can be readily adapted to the scenario of partial centralized treatment, followed by optimized selection and placement of advanced treatment technologies to meet specific more stringent consumer water quality needs. The analysis described here invokes a systems-level consideration of potable water treatment to support a distributed implementation of advanced technologies to reach water treatment and re-use goals.

The advantages of distributed optimal technology network (DOT-Net) systems as a means for providing superior water treatment for potable use and potential energy recovery have previously been enumerated and detailed [Weber, 2002; 2004]. The principal economic driver supporting implementation of such systems are the costs associated with upgrading large centralized treatment facilities and distribution networks to provide water of a quality that consistently meets increasingly stringent drinking water standards. The prime focus of the research described here is a comparison of such costs to those associated with implementation of the DOT-Net model for advanced drinking water treatment under various scenarios and technical conditions for different system sizes and populations.

While disinfection by-products (DBPs) comprise the specific water quality parameter selected for articulation of the comparative analysis, the general methodology described is applicable to most other water quality measures as well. The approach applies to any scenario where water quality degradation corresponds to water age at point of consumption, or where partial processing of water exists due to financial limitations. Indeed, the approach is applicable in general to any scenario in which existing water quality is insufficient and advanced treatment processes must be selected and located in the most cost-effective manner.

Detailed financial and engineering analyses of centralized and distributed treatment approaches for DBP reduction for various selected water infrastructure configurations are presented. Each water infrastructure configuration constitutes a combination of system treatment technology, system service population, and water source

II. DISINFECTION BY-PRODUCT (DBP) FORMATION MODEL

A basic linear DBP formation model was employed for the study. The model, used to determine required levels of water treatment necessary to reduce DBP precursor materials, is considerably more simple than many other DBP models available (for example, see [Sohn et al., 2004]) but was selected because of its ready applicability to general design and operation cost estimations.

2.1. Linear formation model

The removal of DBP precursor material (*preDBP*) due to advanced treatment processes at a water treatment plant was assumed to follow a multiplicative product model of the form

$$\left[preDBP_{system}\right] = \left[preDBP_{conventional}\right] \times \prod X_i \quad (1.)$$

where $preDBP_{system}$ is the *preDBP* concentration after all treatment processes have occurred, $preDBP_{conventional}$ is the *preDBP* concentration in the treated water after conventional treatment processes, and X_i is the additional treatment fraction of *preDBP* removed by advanced process *i*. The formation of DBP within the distribution network was assumed to follow a basic linear model

$$\left[DBP\right] = kt\left[preDBP_{system}\right] \quad (2.)$$

where *DBP* is the lumped aggregate concentration of disinfection by-products at the point of consumption. For the purposes of this model, total trihalomethane (TTHM) was used as a representative and quantitative measure of *DBP*. The phenomenological rate coefficient *k* reflects the influence of such system variables as pH and temperature, while the residence time *t* is a function of distribution system time. Eqs. 1 and 2 combine to form

$$\left[DBP\right] = kt\left[preDBP_{conventional}\right] \times \prod X_i \quad (3.)$$

DBP formation within the distribution system can thus be reduced by changing system parameters such as pH that are reflected in the reaction rate coefficient, by lowering *preDBP* concentrations from conventional treatment processes, or by adding additional treatment processes for *preDBP* removal at the central water treatment plant.

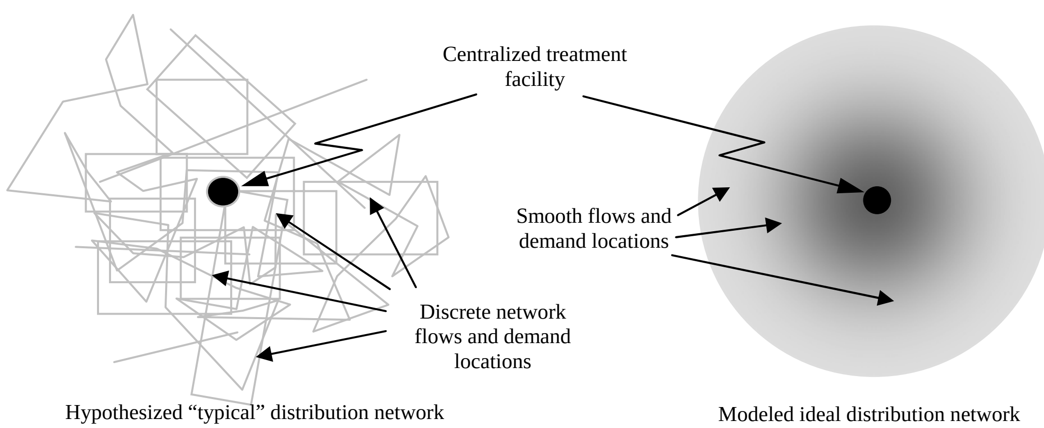

Figure 1. Distribution network model

2.2. Formation rate coefficient

For purposes of this study, a representative TTHM formation rate coefficient of 50 µg/mg (TTHM/TOC)/day was used and was assumed constant throughout the distribution system.

2.3. DBP exposure limits

The US EPA in 1998 established a total trihalomethane (TTHM) exposure limit of 80 µg/L and a haloacetic acid exposure limit of 60 µg/L. For this study, the 80 µg/L TTHM limit was applied as a binding constraint on the maximum TTHM pipeline concentration. This constraint was applied during the optimal selection of additional treatment technologies.

2.4. Residence time distribution

The residence time distribution model employed in this analysis was developed by first idealizing flow patterns within a hypothetical distribution network for a water utility having one centrally located treatment facility. These flow patterns were then idealized as sheet flow treated water discharges from the central treatment location flowing radially outward until consumed by users, as shown in Figure 1.

The residence time distribution was derived with the following assumptions:

1. a single centralized potable water treatment facility;
2. the city can be modeled as a circularly-distributed set of demands;
3. the only inter-network storage volume is capacity within the distribution system pipeline, (i.e. no holding tanks or standpipes exist);
4. the distribution system pipe decreases in volume linearly with distance from the centralized treatment facility;
5. adequate mixing occurs within the distribution system so that discrete pipes can be modeled as a smooth surface; and,
6. demand locations are small enough that they may be modeled as a uniformly smooth surface.

The increase in residence time through any particular segment of distribution pipe follows the equation

$$dt = \frac{V_s}{D_s + Q_s} \quad (4.)$$

where V_s is the storage volume of the segment, D_s is the demand at that segment, and Q_s is the remaining demand past that segment. The storage volume V_s at segment *s* varies as a function of distance from the treatment utility and represents the pipe volume per unit area as follows

$$V_s = \left(\frac{volume}{area}\right) * (area) = \left[(V_{\max} - V_{\min}) \left(1 - \frac{r_s}{r_{\max}}\right) + V_{\min} \right] * [2\pi r_s dr] \quad (5.)$$

where $V_{\max}$ is the maximum storage volume per area associated with the pipes adjacent to the treatment facility, $V_{\min}$ in the minimum storage volume per area associated with the pipes adjacent to the edge of the distribution network, r_s is the distance from segment *s* to the treatment facility, $r_{\max}$ is the radius of the entire distribution network, and *dr* is the length between connections. Note the difference in units between the V_s and the V_{max} and V_{min} values.

The demand at segment *s* can be modeled as

$$D_s = P_s q_c \left(2\pi r_s dr\right) \tag{6.}$$

where P_s is the population density at segment *s*, and q_c is the demand per capita. The remaining demand past segment *s* is

$$Q_s = \pi\left(r_{\max}^2 - r_s^2\right) P_s q_c \tag{7.}$$

Substituting Eq. 5 through 7 into Eq. 4 yields

$$dt = \frac{\left[\left(V_{\max} - V_{\min}\right)\left(1 - \frac{r_s}{r_{\max}}\right) + V_{\min}\right] * \left[2\pi r_s dr\right]}{P_s q_c\left(2\pi r_s dr\right) + \pi\left(r_{\max}^2 - r_s^2\right) P_s q_c} \tag{8.}$$

Eq. 8 was solved numerically by letting ($dr = \Delta r$) where Δr was set to 0.042 miles, a typical length between connections. The values for $V_{\max}$ and $V_{\min}$ were found by using EPA distribution network data concerning pipeline length and size, and US census data to determine average population density P_s for urban settings [Census, 2005; EPA 2002]. For the purpose of this study, an average population density of 5,000 people per square mile was used. Average storage coefficients ranged from 0.5 million gallons/square mile for the largest cities greater than 500,000 people, to about 2.5 million gallons/square mile for cities with a population less than 50,000, as shown in Figure 2. The average length between connections was found by dividing the total length of pipeline within the distribution network by the number of connections within the network. Per capita demand was determined using EPA water system survey data [EPA, 2002]. An example residence time distribution for a hypothetical city is shown in Figure 3. Figure 3 shows the hydraulic residence time calculation for a hypothetical city three miles in radius, with a population density of 5,000 people per square mile, an average connection water demand of 165 gal per day, an average network storage capacity of 1.75 million gallons per square mile over the entire distribution network, and the ratio of maximum to minimum network storage capacity varying as shown. The hydraulic detention time at the perimeter ranges from under nine days to over twenty days. This

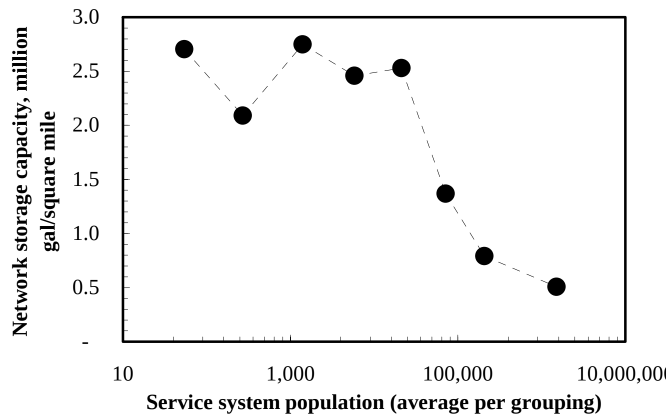

Figure 2. Network storage capacity vs. system size

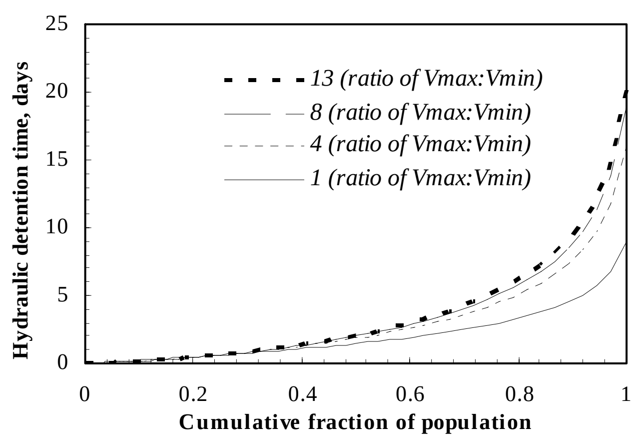

Figure 3. Peripheral storage value sensitivity analysis

data indicates that there is fairly limited sensitivity to hydraulic residence time due to variation in network storage capacity from the center of the network to the periphery of the network for higher ratios of maximum to minimum network storage capacity. For purposes of this study, a 21-day periphery residence time was used.

III. WATER TREATMENT UNIT PROCESSES FOR DBP PRECURSOR REMOVAL

Representative water treatment processes were selected to represent a baseline treatment of TTHM formation potential. Additional treatment technologies were selected to

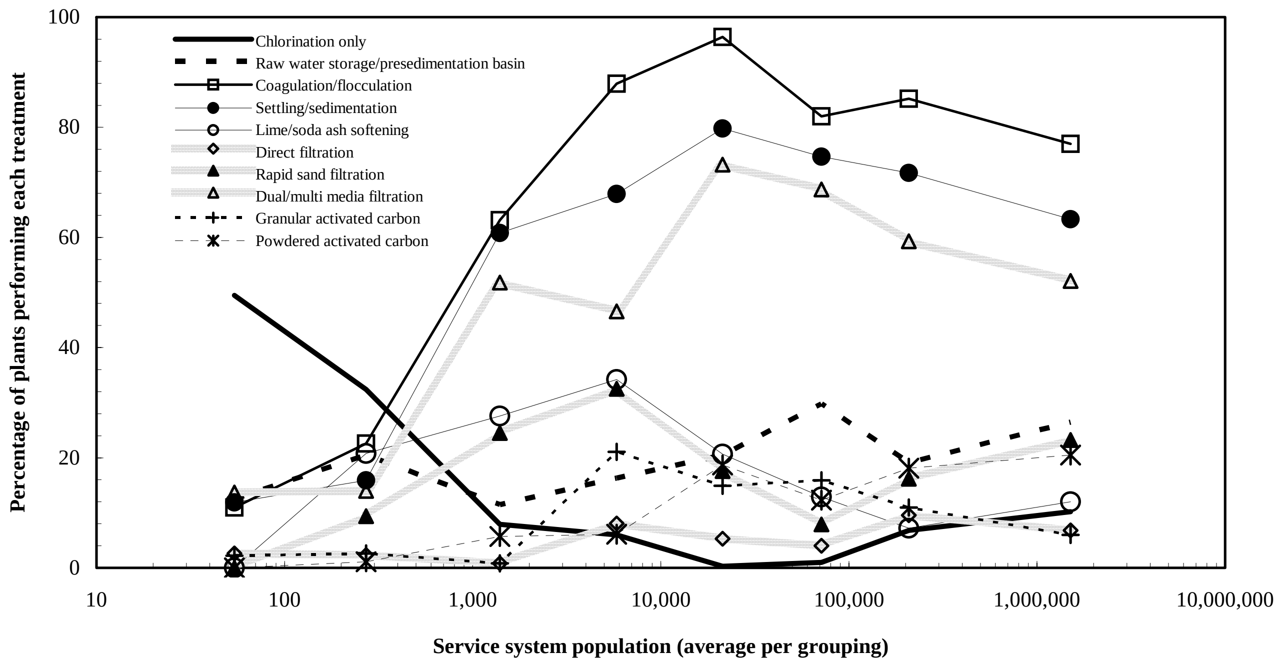

Figure 4. Treatment practices for primarily surface water plants

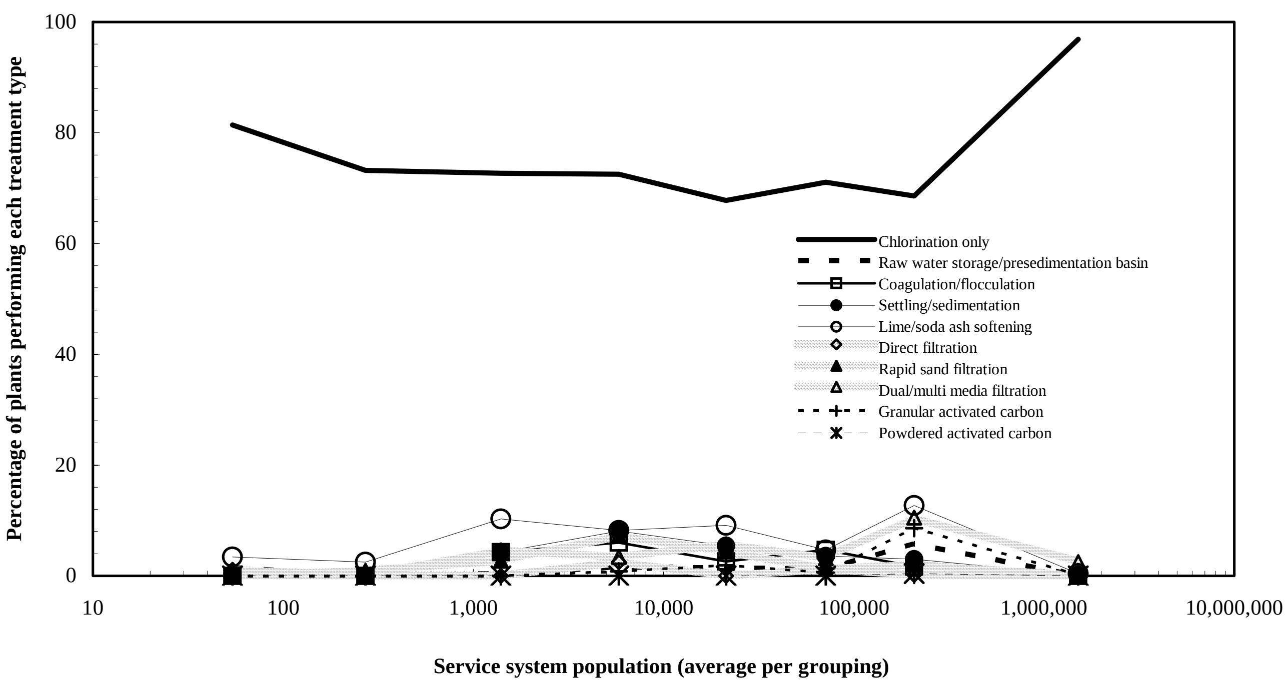

Figure 5. Treatment practices for primarily ground water plants

represent advanced water treatment based on superior removal of TTHM formation potential. The following two sections describe the methods used to select these technologies and to estimate suitable treatment and cost parameters.

3.1. Typical conventional potable water treatment processes

The primary water treatment processes used for potable water treatment were selected using the US EPA Community Water System Survey: 2000 [EPA, 2002]. The principal treatment practices for surface water plants and ground water plants for various system sizes are displayed in Figure 4 and Figure 5. The smallest surface water utilities, those serving less than 500 people, primarily use chlorination as their only treatment, as shown in Figure 4. Between 60 to 95 percent of the surface water utilities serving populations larger than 1,000 people use coagulation and flocculation in their central treatment plants, and between 60 and 80 percent of this same population use settling and/or sedimentation. Between 45 to 75 percent of the surface water utilities serving more than 1,000 people have dual or multi-media filtration, while 7 to 33 percent use rapid sand filtration. Less than 10 percent of those utilities serving more than 1,000 people use direct filtration within their treatment plants.

By comparison, survey data of water utilities using primarily ground water sources reveal very different treatment technology use patterns, as illustrated in Figure 5. More than 65 percent of all ground water utilities use chlorination as their only treatment method, and few technology types are used by more than 10 percent of the treatment plants. Most comment treatment practices for ground water utilities are lime/soda ash softening processes, used by approximately 10 percent of the utilities serving between 500 and 500,000 people, and either direct filtration, rapid sand filtration, or dual/multi-media filtration, generally used by 2 to 5 percent of utilities. The largest ground water utilities, those serving populations greater than 500,000, generally use the fewest treatment types of any utility type or size, with only 0.4 percent using lime/soda ash softening processes and only 2.5 percent using any type of filtration (in this case, duel/multi-media filtration).

For this study, several representative water utility types were selected for economic analysis. These utility types were representative of the most likely technology selections for recycled water utilities respectively, as shown in Table 1. Two types of surface water treatment processes and one ground water treatment process are represented. Each treatment type had an estimated treated water TTHM precursor concentration associated with it, as shown.

Table 1. Selection of representative existing treatment technologies

Initial water source	Centralized treatment processes	TTHM precursor concentration (in treated water)
Surface	Coagulation/Flocculation, Settling/Sedimentation, Duel/Multi-media Filtration	3 mg/L
Surface	Coagulation/Flocculation, Direct Filtration	5 mg/L
Ground	Lime/Soda Ash Softening	1 mg/L

3.2. Potential advanced treatment process upgrades and additions

Five main technologies were selected as potential technologies to treat TTHM precursors to levels that would meet TTHM exposure limits. These technologies are enhanced coagulation, reverse osmosis, granular activated carbon, lime/soda ash softening, and nanofiltration. Each technology treatment effectiveness, along with the capital cost and operations and maintenance cost scaling coefficients, is displayed in Table 2. The TTHM precursor treatment effectiveness for various unit processes was obtained through a literature review. These data are characteristic data used for the purposes of this study and are not meant to be representative of the applicable treatment effectiveness under all environmental and process conditions. The capital, operations and maintenance costs were developed using surveys data obtained from comprehensive EPA cost studies. Capital cost data was obtained from the 2001 EPA Drinking Water Infrastructure Needs Survey [EPA, 2001].

The capital costs of enhanced coagulation were assumed to be a combination of the separate capital costs of the rehabilitation of the sedimentation/flocculation process, the construction of new mechanical waste handling and treatment equipment, and the rehabilitation of a conventional filter plant to handle the increased solids load.

IV. ANALYSIS AND RESULTS

4.1. Hydraulic detention time

The hydraulic detention time was modeled using an approach which assumed that a water utility distribution network could be modeled as a smoothly distributed circular system. Our hydraulic detention time model used five inputs to estimate the hydraulic detention time at any point in the distribution network. These inputs are network radius, population density, demand per capita, central network storage volume, and periphery network storage volume. In order to demonstrate the sensitivity of the model, the maximum hydraulic detention time was calculated for a simple case, as shown in Figure 6. The basis population density was assumed to be 5,000 people per square mile for a total estimated population of approximately 141,400. The per capita daily water demand was assumed to be 165 gallons per person. The central network storage volume was assumed to be 1.75 million gallons per square mile and the ratio of central to periphery network storage coefficient was kept at 10. The segment length was approximately 210 ft. (0.042 miles), while the service area was maintained at a constant six miles across.

Table 2. Treatment efficiency and cost coefficients for advanced technologies

Technology	TTHM precursor removal, percent	Capital cost scaling coefficients		Operations and maintenance cost scaling coefficients		References
		Linear coefficient	Exponential Coefficient	Linear coefficient	Exponential Coefficient	
Enhanced coagulation	55	178,079, 684,895, 768,107	0.56, 0.494, 0.606	156,793	1.00	(Holmes and Oemcke, 2002; EPA, 2001; St. Johns, 1997)
Reverse osmosis (RO)	95	2,330,526	0.814	753,876	0.712	(EPA, 2001; Survey, 1997; Escobar et al, 2000)
Granular activated carbon (GAC)	51	485,010	0.832	206,253	0.5294	(Holmes and Oemcke, 2002; EPA, 2001; Background, 1999)
Lime/Soda Ash softening	31	2,592,446	0.884	305,895	0.7628	(EPA, 2001; Liao and Randtke, 1986; Kissimmee, 2000)
Nanofiltration	90	485,010	0.832	940,156	0.5068	(EPA, 2001; Background, 1999; Schafer et al., 2004; Frimmel et al., 2004)

Figure 6 shows a sensitivity analysis of water age for each input variable. Each variable was varied through a range from 90 to 110 percent of the base value. Population density and demand per capita were found to have an identical impact on water age because both values are used to calculate system withdraws and an increase in either one causes an identical increase in the unit system demand. As a result, they were combined into a single variable called demand per area, which calculated to be 825,000 gal./mile^2. As the demand per area was increased, the water age decreased approximately linearly at almost the same rate of change. For instance, after the demand per area was increased by ten percent, the water age decreased by approximately 9.1 percent. As the network storage volume increased, the water age increased approximately linearly at the same rate of increase, so that a ten percent increase in average network storage coefficient resulted in a ten percent increase in water age. Finally, we found when the ratio of ratio of central to periphery network storage coefficient was increased, the water age increased, but at a much slower rate. After the ratio of central to periphery network storage coefficient was increased by ten percent, the hydraulic detention time increased approximately 1.4 percent.

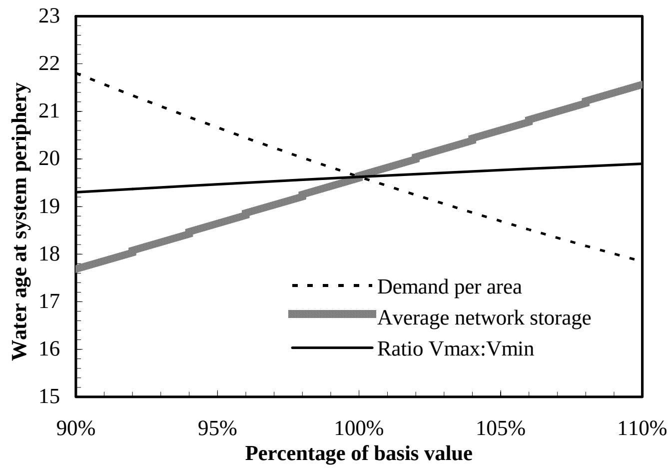

Figure 6. Sensitivity of HDT to input variables

The extreme hydraulic detention time was calculated as a function of total population of the water utility service area (data not shown) using the system data averages from the EPA Community System Survey [EPA, 2002]. For all variations in service population, the 95th percentile water age was found to be quite similar, e.g. in the example data for Fig. 6 above, the 95th percentile water age was nearly 11 days. The extreme water age varied from the greatest value of about 24 days for the smallest networks, those serving a pollution of less than 100 people, to close to 20 days for the largest networks, those serving more than 500,000 people. The reason for the variation in extreme hydraulic detention time is that the model is actually modeling a discrete system withdraw with discrete segment length between connections. The average segment length between connections does not decrease below a finite value, approximately 564 feet for systems serving between 3,300 to 10,000 people to 66 feet for the largest systems serving greater than 500,000 people. As a result, the last few segments at the periphery of the distribution system add a non-proportionally large amount to the hydraulic detention time. The smaller the system, the larger the overall fraction of time added at the periphery, and so the larger the effect of the last segment. This effect impacts the hydraulic detention time of just the last few percentile of the service population. The hydraulic detention time as a function of cumulative population of the service area is the same for all service populations until the last one or two percent of the service population. Note that different service populations might have variations in relative difference in network storage values between the center and periphery, similar to the variations in average network storage value, shown in Figure 2, for different water utility sizes.

4.2. TTHM formation

By combining the TTHP formation potential model with the hydraulic detention time model, we were able to estimate the TTHM concentration at any point within the distribution network. For each system classification type (see Table 1) we assumed an average DOC treated water concentration as shown. At a TTHM formation rate of 50 ug/mg TTHM/DOC per day, our DBP formation model indicated that TTHM will be formed in excess of the EPA TTHM exposure limits in the drinking water between 0.32 to 1.6 days, depending on initial TTHM precursor concentration. In order to meet DBP exposure requirements for the entire population, the each plant will need to decrease DOC to achieve 0.075 mg/L in the final treated water. No single advanced treatment process has been shown to reliably achieve this removal efficiency on a sustained basis, so a combination of treatment technologies will be required.

4.3. Centralized optimal unit process selection

Each advanced treatment technology was analyzed using both capital and operations and maintenance (COM) costs, as well as DOC removal effectiveness, using the data shown in Table 2. The technologies were analyzed for their ability to meet the TTHM requirements and selected based on minimum costs. The present worth of operations and maintenance costs were calculated by using a 20 year design life and 7 percent interest. The optimal technology was selected for water utilities of different sizes using an integer linear optimization method which minimized present worth cost of the selected technologies while holding the required percent DOC removal treatment requirement as a binding constraint.

Figure 7 shows the minimum present worth cost of the technology improvements necessary to meet the EPA TTHM exposure requirements for various existing TTHM precursor concentrations. The minimum cost of the optimum technology increases quite rapidly for the smaller water utilities, but then increases less rapidly for the largest water utilities, as expected for systems exhibiting economies of scale. The data in Fig. 7 are presented on a log-log scale, and exhibit high correlation coefficients ($R^2 > 0.99$) between cost and capacity despite being the combination of several different technologies.

For water utilities with 1 mg/L TTHM precursors (requiring treatment to achieve a 92.5% reduction) reverse osmosis was the optimal technology selection for all plant sizes. For utilities with 3 mg/L TTHM precursors (requiring treatment to achieve a 97.5% reduction) a combination of reverse osmosis and enhanced coagulation was the optimal technology selection for utilities treating up to 11 MGD, while reverse osmosis and granular activated carbon was the optimal technology selection for utilities treating more than 11 MGD. For systems with 5 mg/L TTHM precursors (requiring treatment to achieve a 98.5% reduction) a combination of reverse osmosis, enhanced coagulation, and granular activated carbon was the optimal technology selection for utilities treating up to 11 MGD, while reverse osmosis and nanofiltration was the optimal technology selection for utilities

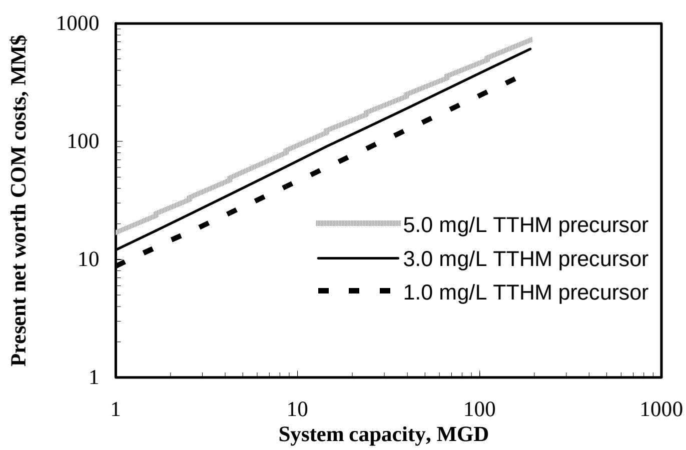

Figure 7. Optimized technology

treating more than 11 MGD.

4.4. Distributed treatment systems – unit costs

The break-even COM costs of distributed treatment systems was calculated by dividing the estimated cost of the required central treatment facility upgrades by the number of residential connections receiving water with DBP concentrations in excess of regulatory limits. This calculation was based on the required number of connections receiving water which needed additional treatment. For example, if fewer connections receive water requiring advanced treatment then the centralized cost will be divided among fewer connections and break-even cost will increase. The break-even cost represents the maximum expense (in present value cost including capital, operations and maintenance costs) that can be spent for each distributed unit and still cost less than or equal to the cost of the centralized treatment system upgrade.

Only residential connections are considered in each scenario. Non-residential demands such as industrial or commercial uses are assumed to receive water treated only by the central treatment facility. The break-even cost per 10 connections, is shown in Figure 8, with system size plotted on a log scale. The break-even cost of treating ten connections, instead of single point-of-entry (POE) connections, was chosen as a more realistic implementation of distributed treatment units. The variation in the plots across varying system size is due to using real data on number of residential connections for different system populations, as reported by EPA system survey results [EPA, 2002].

The cost trends in Figure 8 reveal a decreasing break-even cost for each unit as total water utility service population increases in size. These estimates describe the outlay available to purchase and install, operate, and maintain each distributed unit for a 20 year period with seven percent interest. There are two factors influencing the money available for each distributed unit, the scale efficiency of the centralized treatment system upgrades and the relative fraction of residential connections present within various system sizes. The scale efficiency of the centralized treatment system upgrades tends to reduce the money available per distributed unit because as the water utility size increases, the upgrades cost less per unit volume resulting in less money per treatment unit. On the other hand, as system size increases, the relative fraction of residential connections decreases, so there are fewer connections that need distributed treatment systems. The combination of these two influences tends to be a moderately downward trend of the per unit cost as water utility size increases.

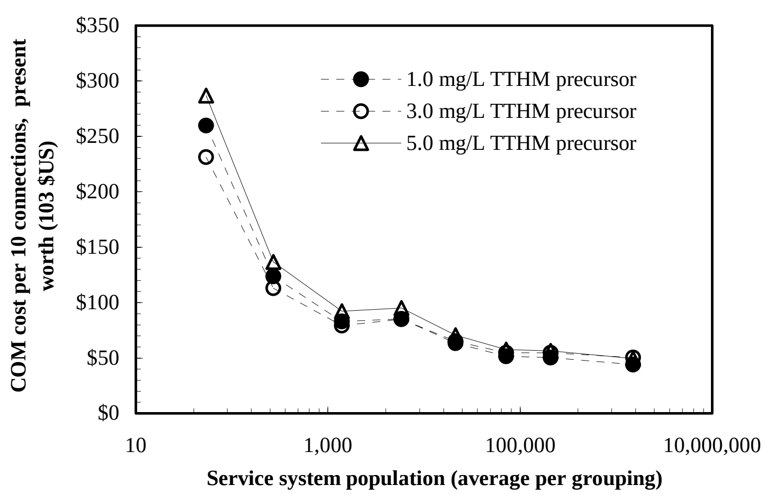

Figure 8. Distributed system unit costs

Note the interesting lack of correlation between TTHM precursor concentration and break-even unit costs, and the general closeness of the distributed unit costs despite the variation in initial water quality. Although the highest TTHM precursor concentration had the highest break-even unit cost for most of the systems sizes, it did not have the highest break-even unit cost for the largest system size examined. Instead, the maximum cost switched to the system with the 3 mg/L TTHM precursor concentration. In addition, there is cross over of greatest unit cost between the 1 mg/L TTHM precursor concentration and 3 mg/L TTHM precursor concentration for smaller service populations. The reason these break-even costs switch back and forth is that they track so closely, and the reason that they track so closely is that there is a balance between the cost of treating a more concentrated flow of TTHM precursor concentration and the formation time it takes for the DBP to exceed regulatory limits. The higher the TTHM precursor concentration the quicker the network DBP concentration exceeds regulatory levels, and thus the higher the fraction of impacted connections within the distribution network. As a result, although a higher TTHM precursor concentration resulted in a larger centralized treatment cost, this centralized cost is divided among more connections and as such the ***per unit*** break-even cost remained fairly constant despite variations in pre-treatment water quality.

V. DISCUSSION

The work described in this paper combines a TTHM formation model with a network hydraulic detention time model to estimate costs required for water utility treatment upgrades needed to meet EPA specified TTHM exposure limits. The hydraulic detention time of water in the periphery of a typical water utility distribution system was found to be quite high, the 95th percentile being about 11 days, while the extreme case typically ranged from about 19 to 24 days, depending on the system size and characteristics. Based on our model, more than half of a typical water utility service population receives water containing TTHM concentrations in excess of EPA regulatory limits. Because of the long detention time, for an average system the treated water TTHM precursor concentration must be reduced to approximately 0.076 mg/L.

The centralized treatment requirements needed to address varying concentrations of TTHM precursors within a range of water utility sizes were then assessed using an optimal selection of advanced technologies. The optimal selection of technologies for each water utility size was determined using the treatment requirement as a binding constraint, and optimizing their selection for any particular system size to obtain minimum costs. The present worth of the estimated capital, operations, and maintenance costs was calculated using a 20-year design life and a 7 percent interest. We found that the costs of the optimum technology selection can be accurately estimated using a log-log linear model with treatment capacity as the variable input, with a residual (r-squared value) of 0.999, even though optimal costs were arrived at via different combinations of technologies over the range of treatment plant sizes investigated.

Finally, for each water utility size, we divided the cost of the estimated central system treatment upgrades by the impacted residential connections to determine the break-even cost of distributed treatment units. Break-even costs for a unit designed to treat 10 connections ranged from $US 260,000 to $US 45,000, with the greatest costs associated with the smallest utilities. We found two primary factors which tend to influence break-even costs: economies of scale and proportion of residential connections. Larger water utilities have an economically advantageous economies of scale and can provide treatment at cheaper per unit volume costs than smaller treatment systems. This influence tends towards a *reduction* in the break-even point as system size increases. However, larger water utilities also have a smaller fraction of residential connections and a larger fraction of non-residential connections; fewer residential connections results in more money available per connection. This influence tends towards an *increase* in the break-even point as system size increases. The combination of these two influences determines the overall break-even unit cost. For the smallest water utilities, where break-even cost is highest, economies of scale dominates and so break-even cost reduces quickly as system size increases. As water utility size increases, the influence of economies of scale starts to become moderated by the reducing proportion of residential connections, causing the break-even point to reduce at an increasingly slower rate. Eventually, for a water utility service population of about 80,000 people, these two forces nearly balance and further increases in utility size result in fairly small reduction in break-even point.

Finally, we found very little difference in break-even costs for varying initial TTHM precursor concentration. Instead we found a fairly close balance between the cost of treating a more concentrated flow of TTHM precursor concentration and the number of residential connections impacted by excess DBP concentrations. The higher the TTHM precursor concentration the quicker the network DBP concentration exceeds regulatory levels, and thus the higher the fraction of impacted connections within the distribution network. As a result, although a higher TTHM precursor concentration resulted in a larger centralized treatment cost, this centralized cost is divided among more connections and so the *per unit* break-even cost remained fairly constant despite variation in pre-treatment water quality.

The water quality parameters and related details used in this paper reflect an optimal selection of treatment processes to address a particular model application scenario in which water quality degradation occur primarily within the distribution network. It is important to recognize however that the approach employed is applicable to any scenario in which existing water quality is insufficient and advanced treatment processes must be selected and located in the most cost-effective manner.

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