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## **MEAN ESTIMATE DEFICIENCIES IN WATER QUALITY STUDIES**

by  
**Barry J. Adams and  
Robert S. Gammell**

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Barry J. Adams, Ph.D.  
Assistant Professor of Civil Engineering  
and Applied Mechanics  
McGill University, Montreal, Canada

and

Robert S. Gemmell, Ph.D.  
Associate Professor of Civil Engineering  
Northwestern University, Evanston, Illinois

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Barry J. Adams and Robert S. Gemmell

### A B S T R A C T

Mathematic models are employed in the design, performance prediction, and evaluation of alternative water quality management programs. This paper examines the relative influence of deterministic and stochastic models on water quality management decisions to demonstrate some deficiencies of decisions based on mean estimates produced by deterministic models. Water quality management problems are examined which consider the implications of variability in waste generation, treatment plant performance, and receiving water behaviour on the resulting variability of water quality. An example is provided in an evaluation of regional wastewater management alternatives given by the size, number, and location of regional treatment plants. It is concluded that an evaluation of water quality management alternatives without consideration for their performance variability may be so deficient as to negate the evaluation. Consequently, water quality information needs for stochastic modelling should be anticipated in the design of water quality surveillance systems and in the analysis of water quality data.

KEY WORDS: Design; Deterministic; Evaluation; Mathematical Models; Performance; Planning; Regional Wastewater Management; Sensitivity; Stochastic; Variability; Water Quality Management.

## MEAN ESTIMATE DEFICIENCIES IN WATER QUALITY STUDIES

By Barry J. Adams<sup>1</sup>, A.M.ASCE and Robert S. Gemmell<sup>2</sup>, M.ASCE

### INTRODUCTION

The use of mathematical models for the design, performance prediction and evaluation of alternative water quality management plans is recognized by the U.S. Government (13) and many water quality management planners (11). The current application of modelling spans a spectrum from the microlevel due to the necessary preoccupation with specific processes of the physical environment to the macrolevel due to current planning methodologies which attempt areawide or basin approaches to functional water quality management planning. Among the modelling decisions facing the water quality management planner are the purposes which models will serve (design, prediction, evaluation), the state of the system being modelled (static or dynamic), the treatment of the modelled system (deterministic or stochastic), and the formulation of the model (analytic or numeric). This paper examines the relative influence of deterministic and stochastic models for design, performance prediction and evaluation on water quality management decisions to demonstrate some deficiencies of decisions based on mean estimates produced by deterministic models and the need for information necessary to formulate stochastic models.

Although engineering and planning practice is recognizing the stochastic nature of the social, economic and physical environments and the performance of engineering systems, the rigorous incorporation of this concept into formal planning, design and evaluation methodologies has been delayed by the only recent mathematical development of stochastic processes and the additional information requirements for stochastic modelling. The appearance of recent studies giving stochastic treatment

<sup>1</sup>Assistant Professor, Department of Civil Engineering and Applied Mechanics, McGill University, Montreal, Canada

<sup>2</sup>Associate Professor, Department of Civil Engineering, Technological Institute, Northwestern University, Evanston, Illinois, U.S.

to water quality management problems is encouraging, but the need remains to expand these concepts to general engineering practice. For example, current water quality standards are frequently based on consecutive periods of low stream flow which implies a probabilistic consideration. Therefore it is inconsistent to neglect the probabilities of other events which affect water quality. It is demonstrated that such neglect may significantly alter the efficiency of water quality management decisions.

With regard to water quality standards, two alternative water quality management plans may result in two different predicted mean water quality responses. To evaluate these alternatives strictly on the basis of mean water quality response is insufficient since water uses are sensitive to the variability of water quality. Figure 1 presents possible water quality probability distribution functions (pdf's) for two alternative management plans. Although the mean response of Alternative 2, level B, is less than that of Alternative 1, level A, the variability of water quality about the mean response is much less in the former case. If level C represents the tolerance limit value for some aquatic species, it is clear from the pdf's that Alternative 1 will violate that level more frequently than Alternative 2. From the point of view of propagation of this species, Alternative 2 is preferable; however, Bella (4) proposes that temporal variations in nutrient supply may be necessary for long-term aquatic ecosystem stability. Thus, the identification of the better alternative is not obvious. This simple example should demonstrate the deficiency of evaluating alternatives solely on the basis of mean performance.

This variability concept is explored in the remainder of this paper through an examination of water quality management problems which consider the implications of variability in waste generation, treatment plant performance or effluent production, and receiving water behaviour on the resulting variability of water quality. Finally, an example is provided in the context of a regional wastewater management problem which considers the size, number and location of regional treatment plants to serve the needs of a water quality management program.

## WASTE GENERATION

Since wastewater management plans must deal with the task of predicting the future generation of wastewaters, the engineer or planner must consider the myriad of factors affecting wastewater generation such as the level of population, the level and nature of activity, and the spatial characteristics of population and activity. Instinctively, the engineer understands that the predicted levels may never become true. He must satisfy himself in that while his prediction may not be the truth, it should be at least close to the truth. The track record for such prediction must leave engineers as an unsatisfied lot (6). The alternative to this process is to recognize and to accommodate the variability of the future. It is in extreme error to design a system whose performance is sensitive to the predicted level of a design variable without consideration for the variance and distribution of variation of that predicted level.

Meier (28) provides an excellent example in the case of population projection. He compares the results of a stochastic population projection technique producing population predictions with confidence bands against traditional projection techniques producing predictions with high-low ranges. The stochastic projections produced not only a more accurate range of estimates but also probabilities of the estimates within the range. As might be expected, the stochastic projection model contains more parameters than traditional models and hence requires more information for the estimation of parameter values. The stochastic components of change model of Meier (28) requires the estimation of 8 parameter values from census data while traditional models require the estimation of as few as one parameter value. Simulation is required for the variance estimation of projected populations since analytic solutions for statistics of complex time dependent phenomena are not generally available. The further refinement of the components of change model to the cohort-survival model or even the multi-regional cohort-survival model further increases the problem of parameter estimation; however, the observations of Berthouex (6) on population forecast error indicate the importance of good probability estimation on population forecasts.

The problem of population projection is one of the long-term future. The treatment plant designer is also concerned with the problems of the short-term future. Even older Sanitary Engineering textbooks discuss the diurnal fluctuation of wastewater flows and strengths. However, few engineering studies incorporate these observations into design practice beyond the consideration of flow equalization chambers. A notable exception is a study by Barthouex and Polkowski (8,9) which proposed plant design including rational overdraft allowances based on the uncertainty inherent in design parameters. One of the major factors inhibiting the application of probabilistic concepts in treatment system design is the lack of information concerning system inputs. In 1971, Wallace and Zollman (39) stated that a request for this type of information in the ASCE Sanitary Engineering Division Newsletter produced only one response. The need for data must be anticipated before data is collected - an engineering responsibility which must be addressed(41).

Input variations to the treatment system will influence the selection, design, and eventual operation of treatment processes. Before the degree to which this influence will extend may be evaluated, plant loadings must be statistically characterized. Wallace and Zollman (39) undertook such a characterization with short time period chemical oxygen demand data concluding that the normalized residuals produced by removing polynomial regression lines were stationary, ergodic and normally distributed. Although this characterization was suggested as a possible technique for simulating plant influent variability, the relatively large number of parameters decreases the transferability of the technique to other locations. McMichael and Vigani (27) demonstrated the value of parametric time series models for predicting influent variability with a minimum number of parameters using the data of Wallace and Zollman (39). It remains for stochastic models of actual influent variability to be employed in an evaluation of its impact on treatment plant performance and how it may be overcome by plant design.



In the context of the regional wastewater management example presented earlier, it would be useful to obtain influent variability characterizations as a function of the generating regions morphology including the size, population density and density distribution. If the degree of variability changes with morphological characteristics such as a generating region's size, decisions regarding the size and number of regional treatment plants would be affected.

#### TREATMENT PLANT PERFORMANCE

As wastewater treatment plants are components of water quality management systems, the performance of such plants must be evaluated by water quality management plans. The performance of conventional wastewater treatment plants has been shown to be highly variable (1,37). The variability of system inputs is inherited by the treatment plant producing a variable effluent quality which is in turn inherited by the receiving water producing a variable water quality. Both the treatment plant and the receiving water accept a variable input which, mixed with their own variable behaviour, produce a variable product. If considered, the performance variability of treatment plants will influence decisions regarding the size, number and location of regional wastewater treatment plants as demonstrated by the following example.

Assuming that the time variability of wastewater treatment plant performance, as measured by effluent biochemical oxygen demand (BOD) concentration, may be satisfactorily described as a normal, independently distributed random variable, the variable is completely described by its mean and variance as given by

$$L_t = \bar{L} + s_L \varepsilon_t \quad (1)$$

in which  $L_t$  = effluent BOD at time  $t$ ,  $\bar{L}$  = mean effluent BOD,  $s_L$  = standard deviation of effluent BOD, and the  $\varepsilon_t \rightarrow \text{NID}(0,1)$  = random shocks.

Furthermore, the coefficient of variation of effluent BOD ( $C_{v_L}$ ) decreases with an increase in plant size as given by

$$C_{v_L} = \frac{s_L}{\bar{L}} = a\bar{Q}^b \quad (2)$$

in which  $\bar{Q}$  = the mean plant flow and a and b = coefficients (3). With this information on performance variability, it is instructive to examine the performance of two alternative regional wastewater management systems. Both systems treat the same quantity of waste to the same degree of treatment. One alternative employs a single large plant while the other employs n smaller plants. The effluent variability of the large plant will be proportionately less than that of the smaller plants in accordance with Eq.2; however, this is not the case for the variance of the pooled effluents of the small plants. The variance of the system,  $(s_L^*)^2$ , as distinct from the variance of the plant  $(s_L)^2$ , is determined from the pooled effluents of all plants in the system as indicated in Fig. 2 and is given by

$$\left. \begin{aligned} s_{L_1}^* &= s_{L_1} && \text{for the 1 plant system and} \\ s_{L_n}^* &= s_{L_n} / \sqrt{n} && \text{for the n plant system} \end{aligned} \right\} \quad (3)$$

if the samples from the small plants are statistically independent (29) which is a reasonably good assumption (1). If both alternatives employ the same type of treatment, it may be assumed that the mean performances of large and small plants are equal, such that

$$\bar{L}_1 = \bar{L}_n = \bar{L} \quad (4)$$

Further assuming that each plant in the n plant system treats an equal quantity of wastewater, the substitution of Eqs. 2 and 4 into Eq.3 yields

$$s_{L_1}^* = s_{L_1} = \bar{L} a \bar{Q}^b \quad (5)$$

and

$$s_{L_n}^* = \frac{s_{L_1}}{\sqrt{n}} = [La(\frac{\bar{Q}}{n})^b] / \sqrt{n} \quad (6)$$

in which  $\bar{Q}$  = the total wastewater flow of the region. The ratio of the standard deviations of each system is given by the division of Eqs.5 and 6

$$\frac{s_{L_1}^*}{s_{L_n}^*} = \sqrt{n} n^b = n^{0.5 + b} \quad (7)$$

or

$$s_{L_n}^* = s_{L_1}^* / n^{0.5 + b} \quad (8)$$

The value of the coefficient b is approximately -0.06(3), and assuming n = 32 , Eq.8 becomes

$$s_{L_n}^* = s_{L_1}^* / (32)^{0.5 - 0.06} = 0.2 s_{L_1}^* \quad (9)$$

or equivalently,

$$(s_{L_n}^*)^2 = 0.04(s_{L_1}^*)^2 \quad (10)$$

If the assumptions of this example are satisfied, it is clear from Eq.10 that the variance of the n plant system's performance is only a small fraction of the variance of the one plant system's performance while the mean performances of both systems are identical. A deterministic evaluation of this example of treatment plant performance would not have revealed this deficiency in the performance of highly centralized systems. The repercussion of performance variability would be felt in the water quality of the receiving waters.

#### RECEIVING WATER BEHAVIOUR

There are many behavioural characteristics of a receiving water body that determine its response to pollution loads. In the case of a

stream receiving an organic load, these include the characteristics of the channel geometry, stream flow, BOD and dissolved oxygen (DO) concentrations, temperature, the rates of deoxygenation ( $K_1$ ) and reaeration ( $K_2$ ), and the activity of planktonic and benthic communities. All of these characteristics exhibit variability. Thus, the water quality response of a water body to variable loading and behaviour will in turn be variable. It is necessary to describe and quantify this variability in order to assess its importance in evaluating water quality management plans.

Streamflow is one of the most variable of the above phenomena, and the importance of its variability to management plans has been widely recognized by water quality management planners. Although stochastic models for streamflow simulation are widely used in water quantity studies, models with time scales suitable to water quality studies have only recently appeared (26). The impact of streamflow variability on water quality standards is suggested by expressions of water quality measures during low flow conditions such as the 7 consecutive day - 10 year low flow. A probabilistic water quality standard is inferred but a precise statement of probability measure is avoided. This lack of preciseness hinders the rational construction of water quality standards and hence the rational evaluation of water quality management plans. Updating the basis of water quality standards has not kept pace with developments in our knowledge of streamflow variability. The variability of future water quality standards presents an additional factor for consideration (6).

The variability in the rates of deoxygenation and reaeration of streams has become a topic of study. Kothandaraman and Ewing (19) demonstrated that the critical DO predicted from the DO sag equation is highly sensitive to the values assigned to  $K_1$  and  $K_2$ . Appreciating this sensitivity, they analyzed the variations in  $K_1$  and  $K_2$  data collected by previous investigators and concluded that measurements of  $K_1$  on the Ohio River were random and normally distributed with a mean of 0.173/day (base e), a standard deviation of 0.066/day, and a coefficient of variation

of 38 per cent. Similarly, they concluded that variations in per cent error in the predicted  $K_2$  values for TVA streams using a regression equation with mean depth and velocity of flow as independent variables are normally distributed with a mean of 0 and a standard deviation of 36.8 per cent. Esen and Bennett (14) employed normal distributions for  $K_1$  and  $K_2$  in a random walk model to predict stochastic DO response from organic loads stating that the significant variations in  $K_1$  and  $K_2$  justify a probabilistic analysis of water quality response. Subsequently Yu(44) examined the effects of errors in  $K_2$  estimation on the cost of water quality management plans. He concluded that uncertainty in  $K_2$  values very seriously affects the evaluation of water quality management programs. These observations should cause serious reflection on current techniques used to estimate  $K_1$  and  $K_2$ . Bennett and Rathbun (5) report that a sensitivity analysis of these commonly used  $K_2$  measurement techniques revealed RMS errors of 15-115 per cent. Kiovo and Phillips (16,17) and Shastry et al (32) have presented error minimizing procedures for estimating  $K_1$  and  $K_2$  for both linear and nonlinear systems.

The rates of deoxygenation and reaeration are dependent on the temperature of the receiving water which is also a variable phenomena. In addition to a prominent deterministic annual cycle (18,36,40), there exist stochastic fluctuations about this cycle (26). Similarly, there are stochastic fluctuations about the diurnal cycle of photosynthesis and respiration of plankton and benthic communities which is dependent on temperature and DO and nutrient concentrations (25).

The variations of BOD and DO concentrations in streams and estuaries has been modelled by Thayer and Krutchkoff (35) as a birth-death process and by Custer and Krutchkoff (10) as a random walk process, respectively. These models have been extended to include variable input sources (31,33) but the rates of deoxygenation and reaeration are considered constant. Li(20) and Thomann(38) have analytically established that longitudinal dispersion in streams may significantly affect the BOD and DO distributions due to short term waste input variability.

These observations demonstrate the high variability of receiving water behaviour and the importance of stochastic approaches to water quality modelling.

## WATER QUALITY MANAGEMENT

The variability of waste generation, treatment plant performance, and receiving water behaviour results in a variable water quality response. Thus, the evaluation of water quality management programs must recognize and accommodate this attribute of variability. Over the past decade, many studies have applied systems analysis techniques to the planning of water quality management programs (11). A comparatively small number of these studies have dealt with probabilistic concepts in water quality management. Some notable exceptions are the studies of Montgomery and Lynn (30), Loucks and Lynn (21,23) and Dysart (12). This is in contrast to the level of activity in stochastic water quantity studies (22,42,43).

Montgomery and Lynn (30) developed a simulation model to represent a wastewater treatment system that included the possibilities of employing effluent storage and low flow augmentation. Four alternative systems with combinations of treatment plant, effluent storage, augmentation reservoir and stream components were evaluated in terms of the frequency with which an assigned limiting value of critical water quality are exceeded. This study stands as one of the first to employ a probabilistic evaluation of water quality management alternatives. Loucks and Lynn (21,23) treated a similar problem analytically by describing the stochastic processes as first order Markov chains with values determined from calculated joint transitional probability matrices. This procedure allowed for serial and cross correlation of variables. The evaluation of system operating policies was also made in terms of the frequency of violating water quality levels. Dysart (12) used simulation to demonstrate the need for variable treatment with continuous monitoring and feedback to contend with input and performance variability in meeting water quality standards.

An important water quality management problem which has received limited attention is that of determining the size, number and location of regional treatment facilities. Previous approaches to the problem have been deterministic with its usual formulation as an optimization problem with the objective of minimizing the system cost with or without water

quality constraints (2). Most of these studies have concluded that the optimal regional system is a highly centralized one. This conclusion is largely due to an incomplete water quality evaluation of alternative degrees of centralization. This example is used to demonstrate that a deterministic evaluation of a water quality management problem may differ substantially from a stochastic evaluation of the same problem.

A water quality evaluation of regional wastewater system centralization was undertaken to test the hypothesis that water quality improvement may result from the spatial and temporal variations of wasteloads attributed to decentralized regional systems. The evaluation employed water quality models developed for both deterministic and stochastic analyses. Each analysis considered a set of experiments which involved a determination of water qualities resulting from alternative degrees of regional wastewater treatment centralization as manifested by the number of plants in the system (1-32 plants). As the water quality response is dependent on the length of the stream over which the waste is discharged, and the ratio of streamflow to wastewater flow, a variety of stream lengths (64-384 miles) and dilution ratios (1/1-80/1) were explored. The experiments assumed that the treatment plants were uniformly distributed along the length of the stream and that the total wasteload was uniformly distributed among the treatment plants in the systems.

The deterministic analysis employed a Streeter-Phelps DO sag type of water quality model. For each computer run of the water quality model, each reach of the system was searched for its minimum DO concentration, and the minimum DO ( $DO_{min}$ ) of all reaches was determined. For all stream lengths examined, there was a steady increase in water quality with an increase in the number of plants in the system as illustrated by Fig. 3 for a dilution ratio of 2/1. While water quality improvement is significant at long stream lengths, it is negligible at short stream lengths. Furthermore, the marginal water quality improvement of systems with greater than about 8 plants becomes negligible at all

system lengths explored. Fig. 4 presents a family of curves depicting water quality response for a variety of dilution ratios for the 64 mile stream system. It is evident that the water quality improvement due to disaggregation of plants is greater at smaller dilution ratios and becomes negligible at higher dilution ratios. Again, a breakoff in water quality improvement appears at an aggregation state of about 8 plants.

The deterministic analysis examined the water quality impact of wastewater treatment centralization assuming constant wastewater and stream water quality and quantity variables. This impact is now examined when these variables behave in a stochastic manner. In order to assess the effects of variable wasteloads and receiving water behaviour, stochastic models were employed to generate values for these variables(2). The system was simulated in the temporal framework of the lowest average 7 consecutive-day flow occurring in 10 years, a common flow condition employed by water quality standards. With the stochastic input models included in the water quality simulation model, the minimum DO frequency response of the receiving waters was determined after each set of simulation runs. These simulations were concerned with the day-to-day variability of the system, and each simulation is that of a steady state system. Experiments were again conducted on stream systems of different lengths and dilution ratios. Fig. 5 presents the water quality frequency response functions for the 64 mile stream system at a 2/1 dilution ratio as cumulative frequency distribution functions (cdf's) for the various systems of plants. The general observation is made that the lower the frequency the greater the difference between the minimum DO levels of the single and multiple plant systems. The effect of stream system length on the water quality frequency response of the 1 and 32 plant systems is illustrated in Fig. 6 for a 2/1 dilution ratio. The length of the system does not affect the frequency response of the single plant system. However, with more than one plant in the system, a given minimum



DO level is violated increasingly less frequently with an increase in distance between plants. The mean responses also improve in accordance with the results of the deterministic analysis. The effect of the dilution ratio on the water quality frequency response of the 1 and 32 plant systems is illustrated in Fig. 7 for a 64 mile stream system. It is evident that the variance of the system response for any number of plants decreases as the dilution ratio increases and for any dilution ratio, decreases as the number of plants increases. Correspondingly, there is an increase in the mean response with an increase in dilution ratio or plant number or both in accordance with the results of the deterministic analysis.

A comparison of the conclusions drawn from the deterministic and stochastic analyses of regional wastewater treatment alternatives may prove instructive. The water quality improvements identified by the deterministic analysis were also identified by the stochastic analysis. In the case of long stream lengths, decentralized plant alternatives resulted in an improved mean water quality response and an improved variance of the response. Since decentralized plant alternatives are more likely to be economically favorable for long stream systems, the impact of this observation will be diminished in these situations. However, in the case of short stream systems, the deterministic analysis revealed a negligible water quality improvement by decentralization on the basis of mean response, particularly at high dilution ratios. This is in contrast to the stochastic analysis which revealed the high variance of water quality response produced by centralized systems. This observation is significant in situations of short stream system lengths where the economics of centralization become competitive and centralized alternatives become serious candidates for consideration.

#### SUMMARY AND CONCLUSIONS

The broad objective of a water quality management program is to increase the accessibility and user benefit of a water resource. Since most water uses depend not only on the average water quality but also on the variability of water quality, the evaluation of water quality management alternatives without consideration for their performance

variability is to neglect an important attribute of the system. This neglect may be serious enough to negate the validity of a deterministic evaluation as demonstrated by a regional wastewater management example.

An assessment of the degree of variability in the performance of the system and the sensitivity of planning decisions to performance variability must precede a commitment to stochastic modelling. Examples of the determination of treatment plant performance variability were given (1,37). James et al (15) have presented a study of the relative importance of variables in water resource planning decisions to determine which variables have the greatest relative impact on planning decisions. Such findings may be used as a guide to the allocation of planning resources for studying those variables (34). McCuen (24) demonstrated the value of component sensitivity analysis for selecting alternative water resource management plans that provide the optimal balance between minimum expected cost and project risk due to performance variability.

The modelling effort in water quality management provides a forum for the quantitative consideration of performance variability; the importance of this variability should be recognized and addressed. Stochastic models are not merely a refinement in the precision of the modelling effort but represent system attributes that would be otherwise unconsidered. Consequently, water quality information needs for stochastic modelling should be anticipated in the design of water quality surveillance systems and in the analysis of water quality data.

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## APPENDIX II - NOTATION

The following symbols are used in this paper:

- $a$  = coefficient
- $b$  = coefficient
- $C_v$  = coefficient of variation
- $K_1$  = rate of deoxygenation
- $K_2$  = rate of reaeration
- $L$  = effluent biochemical oxygen demand concentration
- $\bar{L}$  = mean  $L$
- $n$  = number of treatment plants
- $\bar{Q}$  = mean wastewater flow
- $s$  = standard deviation of plant performance
- $s^*$  = standard deviation of system performance
- $t$  = time
- $\epsilon$  = random shock  $\rightarrow NID(0,1)$

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### APPENDIX III - FIGURES



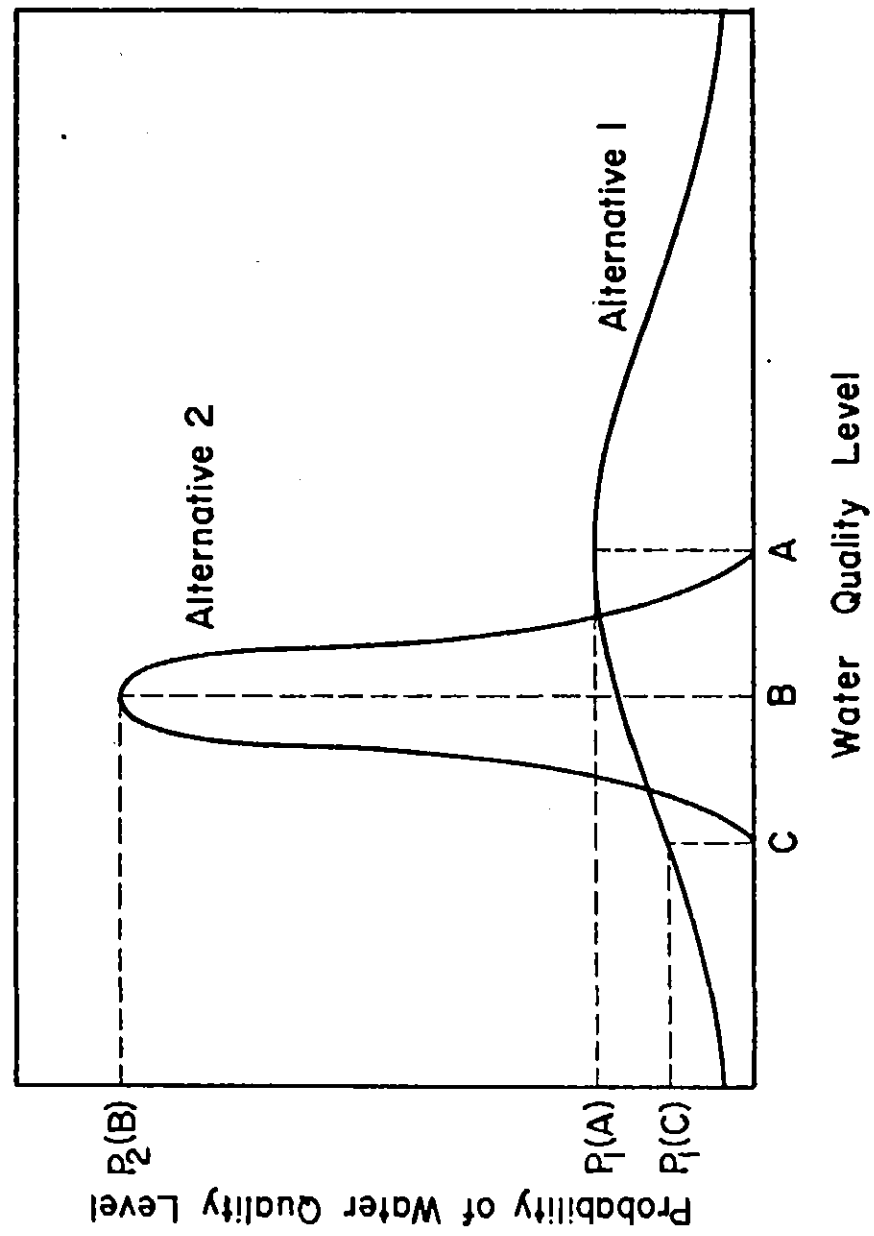


Figure 1. Alternative Water Quality Probability Distribution Functions

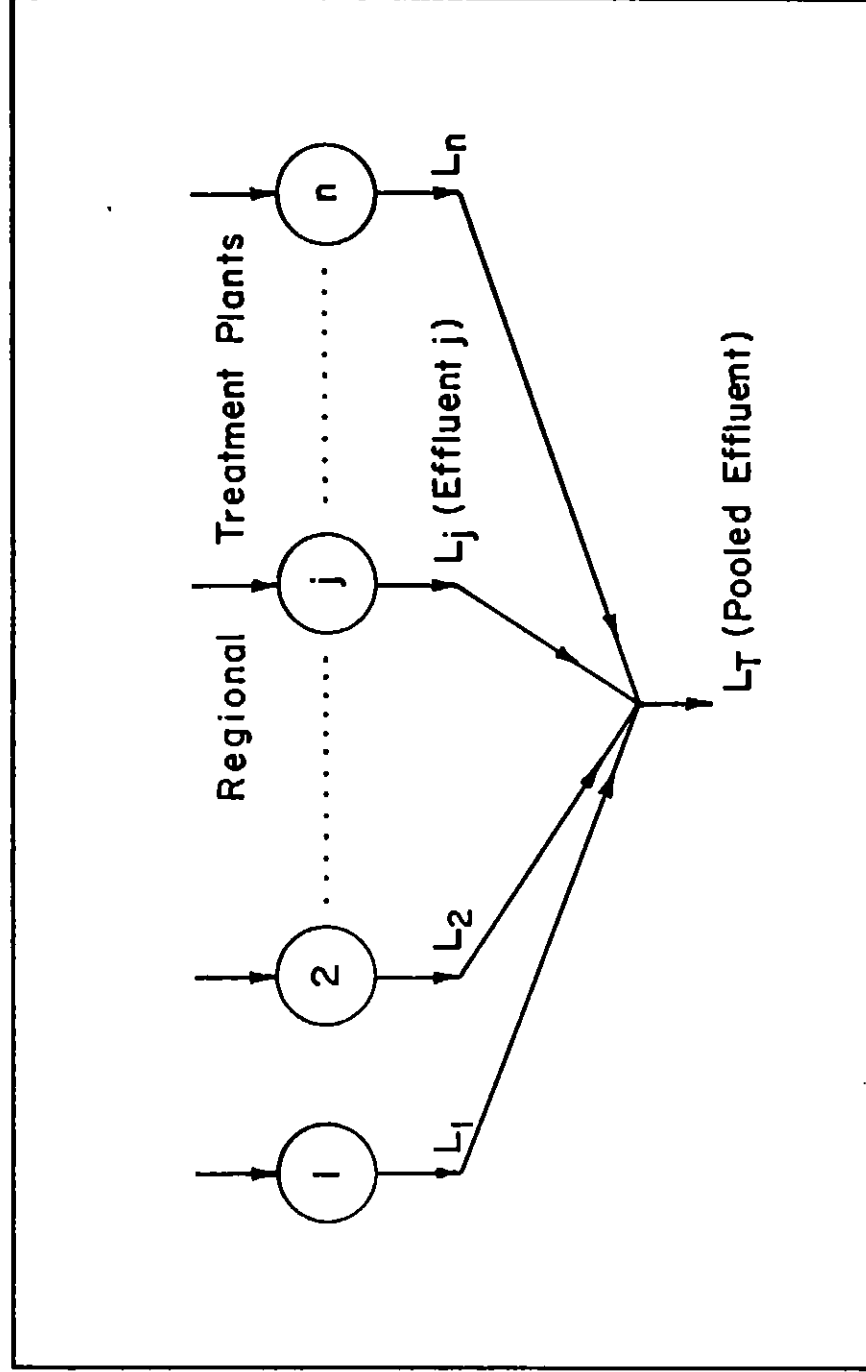


Figure 2. Regional Wastewater Treatment Plant Effluent Aggregation

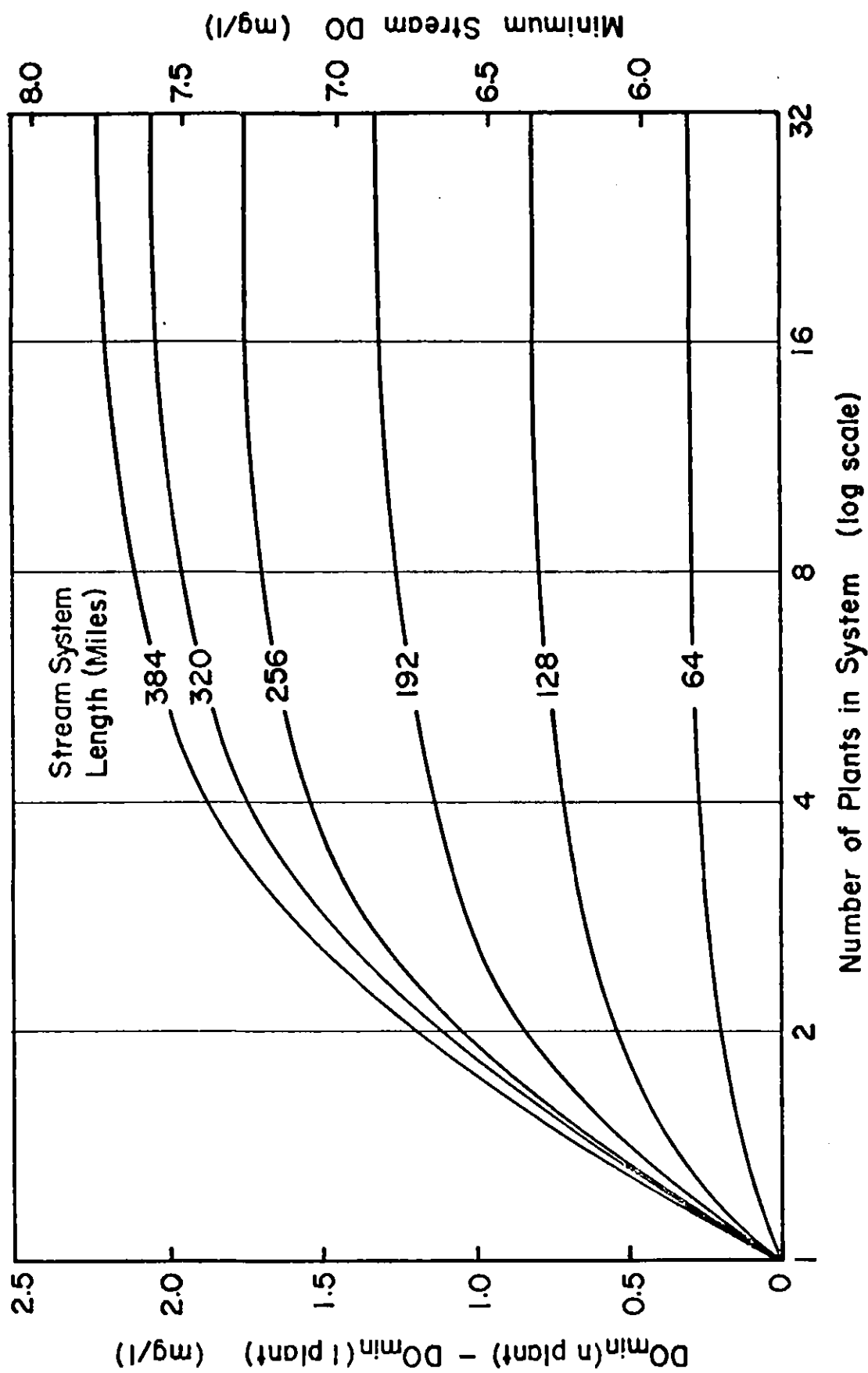


Figure 3. Water Quality Response to Centralization for Various System Lengths  
(Deterministic Model)

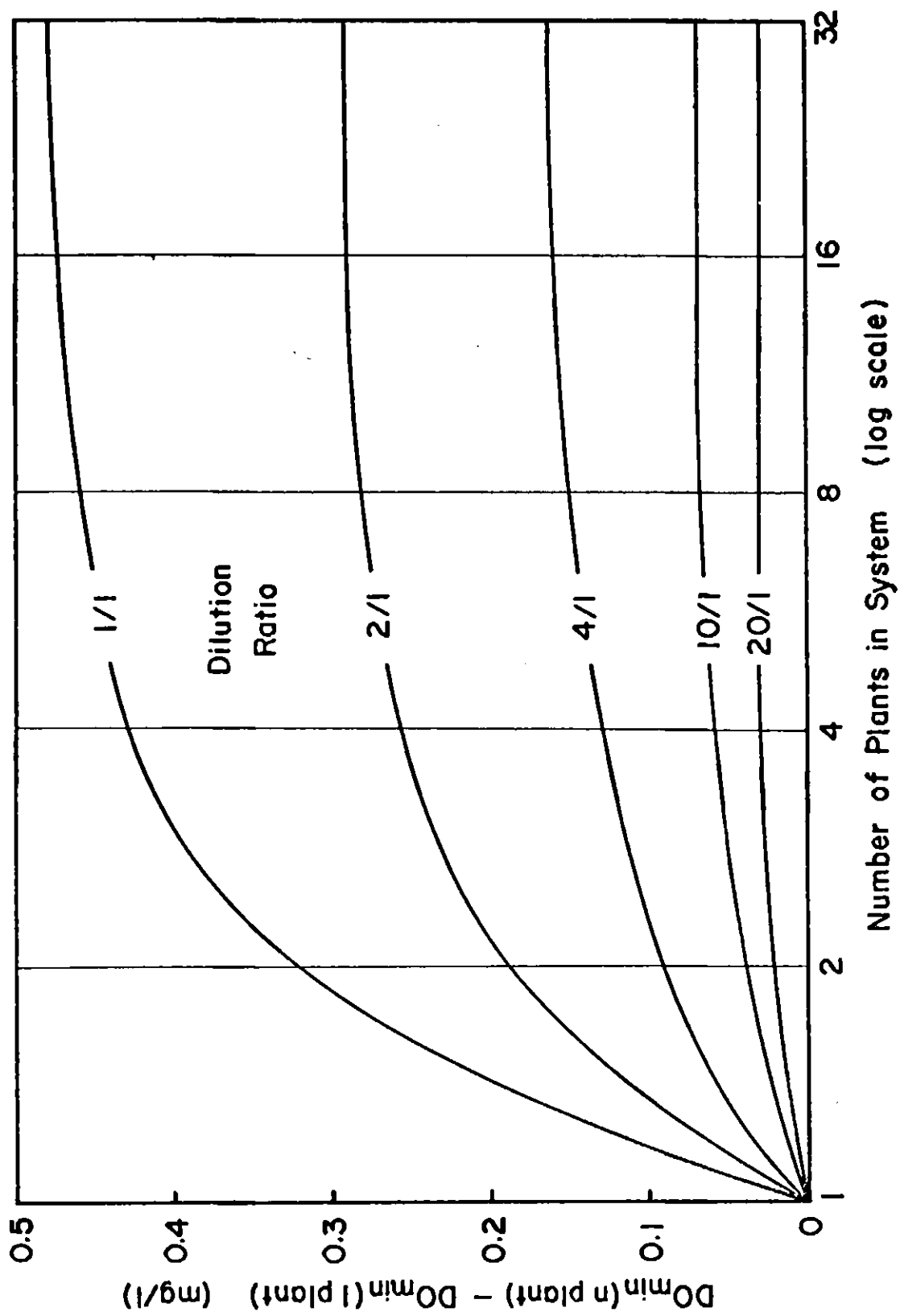


Figure 4. Water Quality Response to Centralization for Various Dilution Ratios.  
(Deterministic Model)

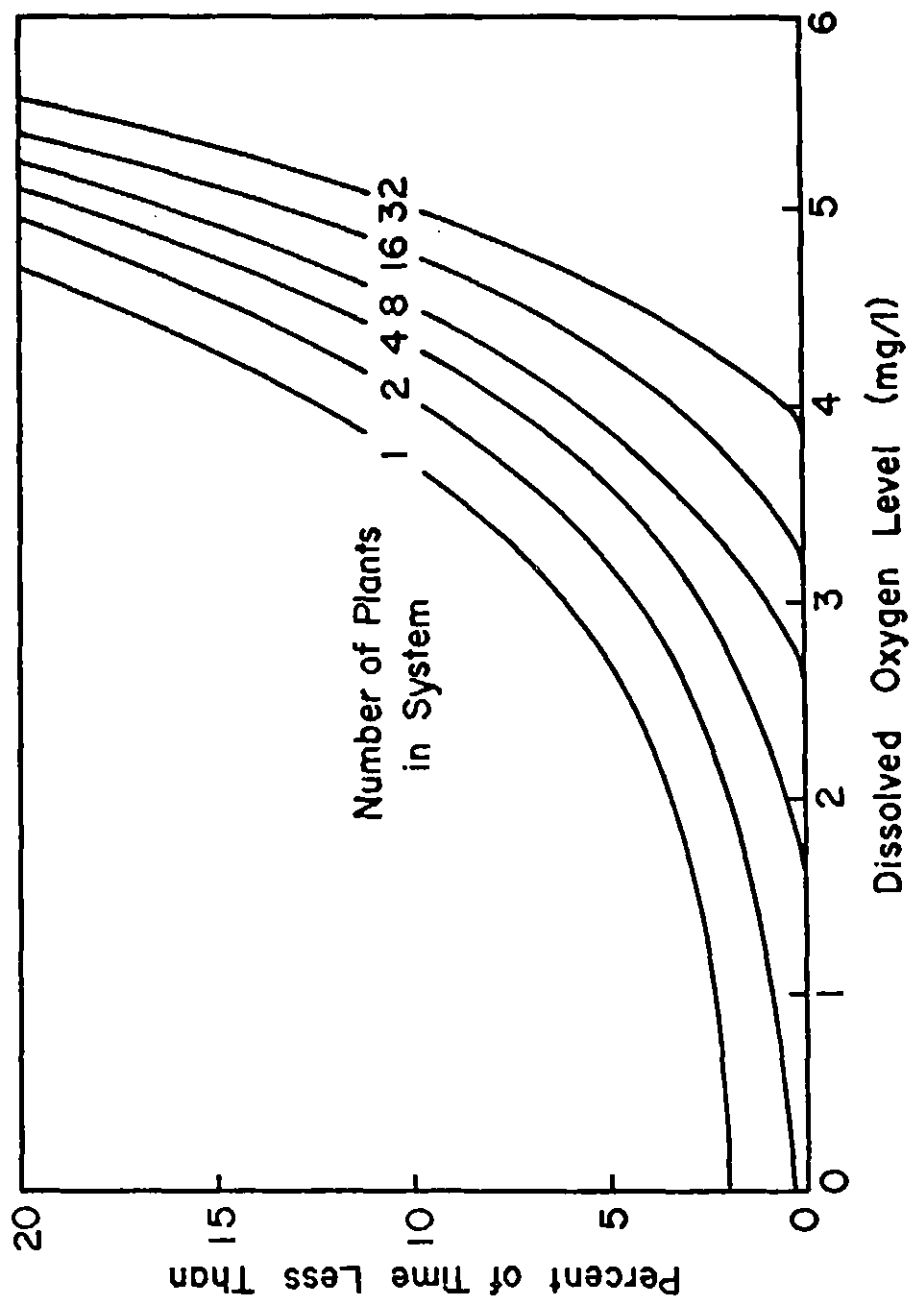


Figure 5. Water Quality Frequency Response to Centralization  
(Stochastic Model)

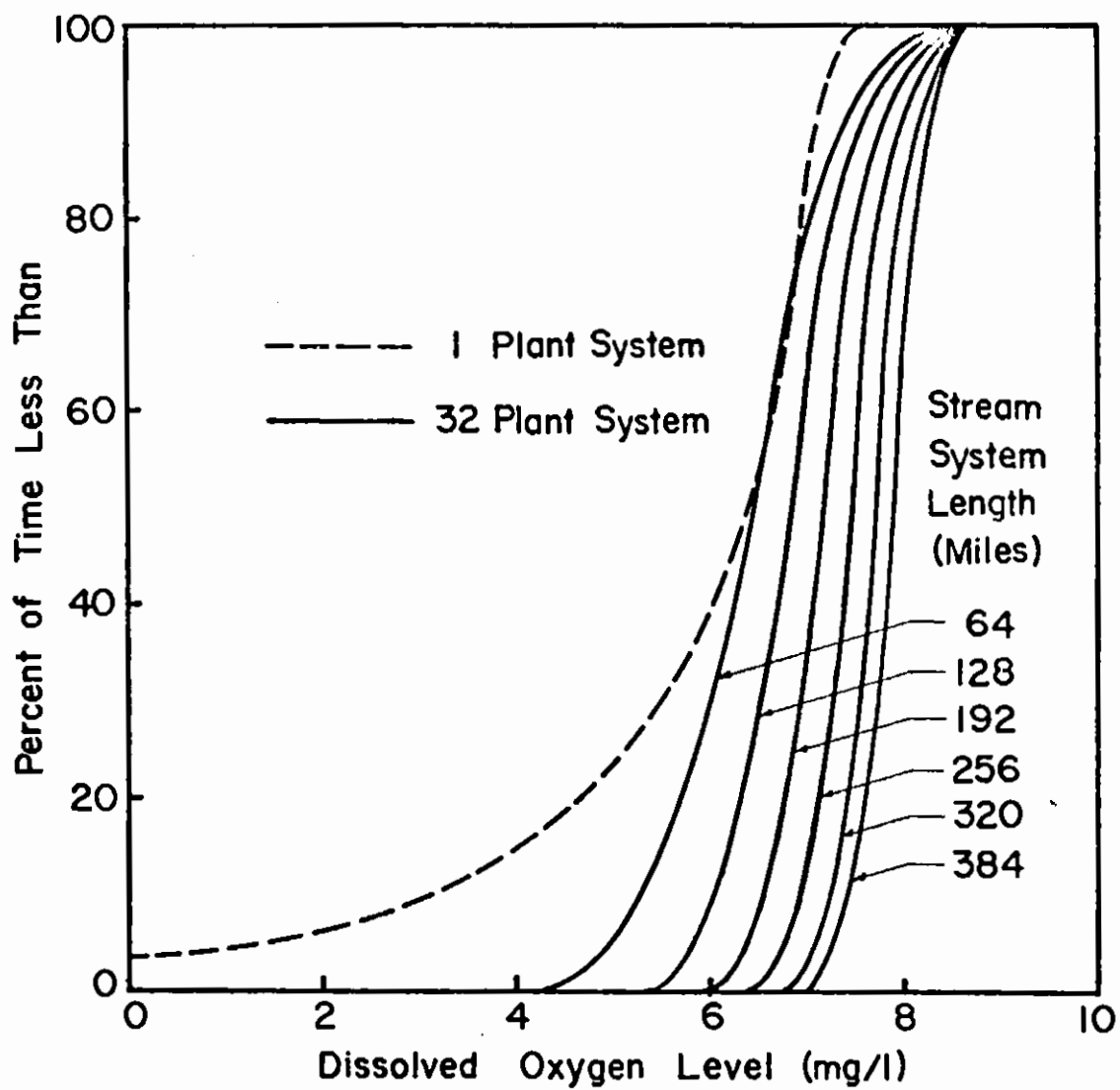


Figure 6. Water Quality Frequency Response for Various System Lengths (Stochastic Model)

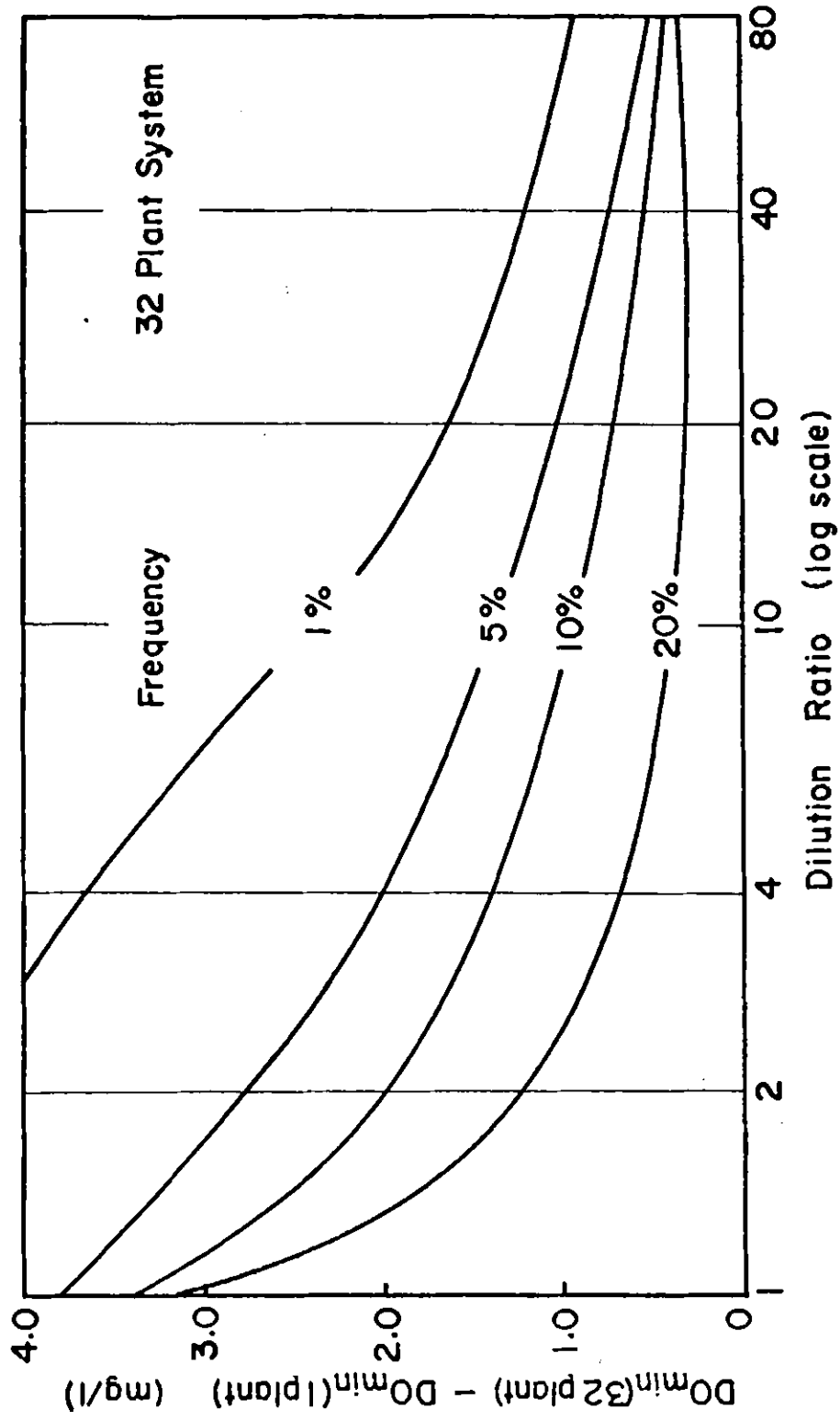


Figure 7. Low Frequency Water Quality Improvement by Decentralization  
(Stochastic Model)