Chapter 14

Integration of Probabilistic and Physically-Based Modelling With Optimization Methods for Stormwater Infrastructure Rehabilitation

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Probabilistic stormwater flows are determined using kinematic wave routing methods and long-term historical rainfall. A multiobjective chance constrained optimization model, subject to constraints based upon physical modelling and historical rainfall data, is applied to a stormwater drainage network in Atlanta, Georgia. The optimization model objectives include minimization of total rehabilitation costs and maximization of stormwater system reliability. Rehabilitation alternatives include replacement, upgrading and varying the design capacity of the drainage system. This modelling approach can be used to develop trade-off relationships between the minimum rehabilitation cost and the probability of failure of the drainage system due to stormwater events. Results of optimization with a simplified runoff model (the rational formula with intensity-frequency-duration curves derived from Gumbel statistical methods) are compared to the results obtained by kinematic routing of stormwater through the channels and pipes of the network, using long-term historical rainfall as input.

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14.1 Introduction

Since the early 1980s, it has been understood that the deterioration of the American infrastructure is an enormous problem (Grigg, 1986). Estimates of the funds required to rehabilitate the infrastructure of the United States are as high as two trillion dollars (ASCE, 1984). Steinthal (1985) indicated that the problem is so immense that even with significant commitments of financial and technological support, problems concerning infrastructure rehabilitation will exist well into the 21st century.

An important component of any modern country's infrastructure is its water supply, stormwater drainage and wastewater conveyance systems. Cost estimates associated with the rehabilitation of American water supply and drainage systems are more modest. In 1982, cost estimates for rehabilitation, expansion and deferred maintenance came to approximately $125 billion for water supply systems, $100 billion for wastewater treatment systems, $35 billion for combined sewer systems and $93 billion for stormwater pollution control (Grigg, 1986). In addition, Grigg (1986) reports these figures consider pollution control only and not flooding problems due to urbanization and other development. Grigg estimates that the resources needed to rehabilitate, expand and properly maintain stormwater drainage systems throughout the United States may exceed $200 billion.

This paper describes the integration of probabilistic and deterministic (physically-based) models with chance constrained optimization to determine efficient replacement and rehabilitation strategies. Chance constrained models are specialized mathematical optimization models in which one or more of the physical constraints is expressed as a probability statement (Jacobs and Wood, 1991). The models developed are integrated into a decision-making tool that determines possible alternative rehabilitation strategies conditioned on probabilistic physical parameters (e.g., rainfall intensity, infiltration rate) of flow routing (e.g., kinematic wave).

The decision model considers multiple rehabilitation alternatives which include upgrading and/or replacement of existing components of the stormwater drainage system. Cost efficient rehabilitation strategies are determined, as driven by flows generated by integrating statistical methods and deterministic kinematic wave models (Wooding, 1965; Yen and Sevuk, 1975; Medina and Mohns, 1978; Medina and Burneson, 1987). This methodology can be used to develop trade-off relationships between the minimum rehabilitation cost and the system's probability of failure due to extreme storm events. A model for optimal long-term scheduling of stormwater drainage rehabilitation was developed earlier, but without physically-based routing (i.e., rational formula) by Jacobs et al. (1993).

14.2 Analysis of the Rainfall Time Series

It has been known for some time that the large number of factors affecting the quality of surface runoff (buildup between storms, washoff, transport, kinetic interactions, etc.) prevents the use of any single event (either synthetic or historical) for proper analysis and design (Heaney et al, 1977). James and Drake (1980) argued that design storms developed from statistical analysis of point rainfall records include all types of rainstorms; consequently, the resultant rainfall distributions are unlike any type of observed rain storm. When the synthetic temporal distribution of rainfall from a design storm is applied uniformly across a catchment, the resulting runoff hydrographs are also unlike observed runoff hydrographs. For receiving water quality, it is not only the frequency response of the system which is significant, but also the durations of the violations (Medina et al., 1981a, 1981b). Regardless of whether water quantity or quality control is the primary objective, long-term historical rainfall data are required (e.g., hourly or shorter-interval precipitation for 30 to 40 years is desirable). The purpose in quantitative analysis of the rainfall time series is to summarize the variables of interest (volume, duration, intensity and time between storm events) and statistically characterize the rainfall record to assess the probability of occurrence of storm events of various magnitudes.

To properly analyze the rainfall time series, storm events must be defined in terms of their statistical independence. A common approach is to derive a minimum interevent time (IET) (Heaney et al., 1977): the minimum dry weather period separating independent wet weather events. Medina (1979) and Medina et al. (1981a, 1981c) computed the autocorrelation function of the rainfall time series, and chose the minimum IET as the point in the correlogram at which an essentially zero correlation first occurs (e.g. within 95% tolerance limits). Restrepo-Posada and Eagleson (1982) proposed selecting an IET such that the intervals between storm event midpoints are exponentially distributed. Trial values of the IET are chosen until a coefficient of variation near 1.0 is finally obtained for the time interval between event midpoints: the method chosen for this study. The IET may vary from six hours in the eastern part of the United States to 300 hours for west coast sites, where rainfall has a pronounced seasonal distribution.

14.3 Model Development

In the kinematic wave approximation, the continuity and momentum equations may be combined into a non-linear, one-dimensional partial differential equation (equation 1). Equation (1) is solved numerically for depth y, as a function of position, time and rainfall minus infiltration: $y=f(x,t,i-f)$. Once y is found, it is substituted into equation (2) to give the flow per unit width. Equations (1) and (2) are for unit width ($A=y$).

$$\frac{\partial y}{\partial t} + m \alpha y^{m-1} \frac{\partial y}{\partial x} = i - f \qquad (1)$$

$$q = \alpha y^{m} \qquad (2)$$

where

$$\alpha = \frac{1.49}{n} \sqrt{S} \qquad (3)$$

and S is the slope, *n* the Manning's roughness and *m* a nonlinear coefficient. The more general case is to solve for flow area *A(x,t)*, including width of overland flow. This model is then extended to the stream-channel and catchment-stream case:

$$\frac{\partial A}{\partial t} + \alpha \frac{\partial A^{m}}{\partial x} = \bar{q} \qquad (4)$$

$$Q = \alpha A^{m} \qquad (5)$$

14.4 Explicit Finite-Difference Solution for Overland Flow

The objective of the numerical solution is to solve for *A(x,t)* at each point on the x-t grid, given the parameters α and *m*, and the initial and boundary conditions. The finite-difference form of the spatial and time derivatives is:

$$\frac{\partial A}{\partial x} \approx \frac{A_{i+1}^{j+1} - A_{i}^{j+1}}{\Delta x} \qquad (6)$$

$$\frac{\partial A}{\partial t} \approx \frac{A_{i+1}^{j+1} - A_{i+1}^{j}}{\Delta t} \qquad (7)$$

To create a linear equation, the value of A used in ($\alpha m A^{m-1}$) is found by averaging the values across the diagonal (A^*). Letting the value of rainfall excess $(i\text{-}f)=q$ (which becomes lateral inflow for the channel-flow case), it is obtained by averaging the values on the $(i+1)^{th}$ distance line. By substituting the above expressions into equation (4), the linear scheme finite-difference approximation to the kinematic wave as modified from Chow, Maidment and Mays (1988) is:

$$\frac{A_{i+1}^{j+1} - A_{i+1}^{j}}{\Delta t} + \alpha\left[\frac{(A_{i+1}^{j+1})^m - (A_i^{j+1})^m}{\Delta x}\right] = \frac{q_{i+1}^{j+1} - q_{i+1}^{j}}{2} = \bar{q} \qquad \textbf{(8)}$$

Solving for the unknown value of A yields:

$$A_{i+1}^{j+1} = \bar{q}\,\Delta t + A_{i+1}^{j}\left[1 - \frac{\alpha\,\Delta t}{\Delta x}(A_{i+1}^{j})^{m-1}\right] + \frac{\alpha\,\Delta t}{\Delta x}(A_i^j)^m \qquad \textbf{(9)}$$

The Courant condition represents a restriction on the relationship between the time step, the distance increment and kinematic wave celerity c_k. This condition is defined by:

$$\Delta t \le \frac{\Delta x_i}{c_k} \qquad \textbf{(10)}$$

$$c_k = \alpha\, m\, A_*^{m-1} = \frac{dx}{dt} \qquad \textbf{(11)}$$

$$\theta = \alpha\, m\, A_*^{m-1}\,\frac{\Delta t}{\Delta x} \le 1 \qquad \textbf{(12)}$$

A second approximation to equation (4) is invoked when the parameter θ is greater than 1:

$$\frac{A_i^{j+1} - A_i^{j}}{\Delta t} + \alpha\left[\frac{Q_{i+1}^{j+1} - Q_i^{j+1}}{\Delta x}\right] = \bar{q} \qquad \textbf{(13)}$$

Solving for unknown Q and then A yields:

$$Q_{i+1}^{j+1} = \bar{q}\,\Delta x + Q_i^{j+1} - \frac{\Delta x}{\Delta t}(A_i^{j+1} - A_i^{j}) \qquad \textbf{(14)}$$

which is mathematically stable if $\theta \geq 1$ and,

$$A_{i+1}^{j+1} = \left(\frac{Q_{i+1}^{j+1}}{\alpha} \right)^{\frac{1}{m}} \qquad (15)$$

14.5 Kinematic Channel Flow

The continuity and momentum equations for kinematic channel flow routing are:

$$\frac{\partial Q_c}{\partial x} + \frac{\partial A_c}{\partial t} = q_0 \qquad (16)$$

$$Q_c = \alpha_c \, (A_c)^{m_c} \qquad (17)$$

Substituting the derivative of Q with respect to x into the first equation above, the continuity and momentum equations may be combined into another nonlinear, one-dimensional partial differential equation:

$$\frac{\partial A}{\partial t} + \alpha_c \, m_c \, A_c^{m_c - 1} \frac{\partial A_c}{\partial x} = q_0 \qquad (18)$$

where q_0 is lateral inflow and flow area A is used as the dependent variable. Note that since hydraulic radius R is equal to flow area A divided by the wetted perimeter P, the channel parameter α_c may be derived from Manning's equation:

$$Q = \left[\frac{1.49 \sqrt{S_0}}{n \, P^{2/3}} \right] A^{5/3} \qquad (19)$$

$$\alpha_c = \frac{1.49 \sqrt{S_0}}{n \, P^{2/3}} \quad and \quad m_c = 5/3 \qquad (20)$$

Channel parameter α is thus a function of Manning's roughness, bed slope and wetted perimeter P. The wetted perimeter depends on the channel type and geometry (e.g. rectangular, triangular, trapezoidal, or circular cross-sections).

14.6 Finite-Difference Linear Scheme

The objective of the numerical solution is to again solve for $A(x,t)$ at each point on the x-t grid, given the channel parameters and the initial and boundary conditions. The outflow hydrograph $Q(x,t)$ is obtained through the stage-discharge relationship. The finite-difference solution scheme is almost identical to that of the overland flow case. To create a linear equation, the value of A used in ($\alpha m A^{m-1}$) is again found by averaging the values across the diagonal (A^*). The value of lateral inflow q is obtained by averaging the values (over time) on the $(i+1)^{th}$ distance line (if there is any overland flow). Solving for the unknown value of A, and then Q yields:

$$A_{i+1}^{j+1} = \bar{q}_0 \, \Delta t + A_{i+1}^{j} \left[1 - \frac{\alpha_c \, \Delta t}{\Delta x} (A_{i+1}^{j})^{m_c - 1} \right] + \frac{\alpha \, \Delta t}{\Delta x} (A_i^j)^{m_c} \quad (21)$$

and

$$Q_{i+1}^{j+1} = \alpha_c \left(A_{i+1}^{j+1}\right)^{m_c} \quad (22)$$

The Courant condition applies as before, with an alternate approximation when θ is greater than 1,

$$\Delta t \leq \frac{\Delta x_i}{c_k} \quad (23)$$

and

$$c_k = \frac{1}{B} \frac{dQ}{dy} \quad (24)$$

where B = channel top width. The kinematic wave celerity is also dependent on channel type and geometry (e.g. circular pipe, rectangular channel).

14.7 Optimization

Using the finite difference solution to the kinematic wave, the optimal rehabilitation model is expressed as a chance constrained model. Mathematically, the general chance constrained model is expressed as:

$$minimize\ COST = \sum_i \sum_j C_{ij} X_{ij} \tag{25}$$

$$minimize\ p_f = 1 - \left[\prod_i (1 - p_{fi}) \right] \tag{26}$$

subject to:

$$p\ (Q_i \le Q_{max})_i \ge 1 - p_{fi} \qquad \forall_i \tag{27}$$

$$Q_i,\ p_{fi} \ge 0 \qquad \forall_i \tag{28}$$

$$x_{ij} \in 0,\ 1 \qquad \forall_{ij} \tag{29}$$

The binary decision variable for implementing a rehabilitation alternative, $\mathbf{X}_{ij}$, is a function of the pipe capacity, $\mathbf{Q}_{max}$. $\mathbf{C}_{ij}$ represents the cost of rehabilitating pipe segment *i* with rehabilitation alternative *j*. $\mathbf{Q}_i$ is the actual flow in pipe segment *i* determined by the kinematic wave model and conditioned upon the randomly selected historical storm events. The terms $\mathbf{p}_f$ and $\mathbf{p}_{fi}$ represent the total probability of system failure and the individual probability of failure for segment *i*, respectively.

The chance constrained model presented here is solved using Monte Carlo simulation in which the storm event is considered to be a random variable with a known distribution. The solution to this optimization problem specifies the rehabilitation/replacement activities throughout the planning horizon. Due to the complexities associated with solving for the overland and pipe flows using a kinematic wave model, the chance constrained model is solved using a heuristic algorithm. The probability of system failure is determined using Monte Carlo simulation in which the complete storm event is considered a random variable selected from historical rainfall data. Rehabilitation decisions are made by systematically upgrading the pipe segment with the highest individual probability of failing. The total probability of failure ($\mathbf{p}_f$) is determined using the weakest link scenario, where the system is considered to have failed if any component within the system fails. The total probability of failure is defined mathematically as stated in the objective function:

$$p_f = 1 - \left[\prod_{i=1}^{n} \left(1 - p_{fi}\right) \right] \tag{30}$$

where p_{fi} represents the probability of failure for pipe segment *i*. Rehabilitation costs are defined as the sum of the rehabilitation cost for each pipe segment being rehabilitated. Figure 14.1 presents a flowchart for the heuristic solution algorithm. An example application using long-term Atlanta rainfall, and an Atlanta stormwater catchment and drainage conduit network, follows below.

14.8 Application to Study Area

14.8.1 Rainfall Analysis

A time series consisting of about 42 years of hourly rainfall at the Atlanta airport first-order station was used as input to the physically-based simulation model. The time series was subjected to a thorough statistical analysis, summarized in Table 14.1 in terms of storm event means and coefficients of variation (COV). Recorded depths for given durations are presented in Table 14.2. The number of events in the record exceeding the Gumbel-type extreme-value depths and intensities is presented in Table 14.3. It is interesting to note that the Gumbel 10-year storm depth (5.5 inches) is only slightly smaller than the 24-hour maximum depth of the 42-year record (5.67 inches). Not surprisingly, use of the rational formula (coupled with intensities derived from Gumbel-type extreme value distributions), results in peak flows for design which are much larger than those obtained by kinematic routing and historical rainfall.

The frequency distribution of rainfall depths is presented in Figure 14.2, showing high frequencies in the smaller rainfall depth intervals. The cumulative frequency, presented in Figure 14.3, illustrates that 90% of the 4329 storms in the record are less than or equal to 1.24 inches (95% are less than or equal to 1.75 inches). As noted earlier, the independence of storm events was determined by iterating until a COV near 1.0 (see Table 14.1) was obtained for time between events (interevent time); for Atlanta, a minimum interevent time of six hours was defined. In other words, at least six hours of dry weather were required to separate independent storm events.

14.8.2 Model Implementation

The Monte Carlo algorithm outlined in Figure 14.1 was implemented using 1000 randomly selected storm events as input to the kinematic wave runoff simulation model. The physically-based (deterministic) model is used to assess the probability of failure of the drainage system. Thus, the actual storm event selected each time is a random variable with a known distribution (derived from the historical rainfall). The pipe most likely to fail is determined with the aid of a sorting routine. The algorithm proceeds to the next iteration. To illustrate the model and solution algorithm described above, consider the stormwater drainage network presented in Figure 14.4. Table 14.4 lists the original design specifications for the components of this illustrative stormwater drainage system. Table 14.5 presents the possible rehabilitation alternatives along with the associated unit cost for each type of drainage pipe used in the network. For this example, it was assumed that the type of pipe used for rehabilitation matched that of the original pipe.

Figure 14.5 illustrates the trade-off relationship between rehabilitation cost and the probability of stormwater system failure. Due to the fact that the implementation of any one rehabilitation alternative reflects a discrete decision, the trade-off relationship comprises a discrete collection of specific rehabilitation strategies. Figure 14.5 clearly indicates that the cost of system rehabilitation increases as the probability of failure decreases. However, these results do not show a smooth trade-off relationship. This is due to the fact that the unit cost of replacing a pipe segment does not follow a linear relationship with respect to available pipe diameters (Figure 14.6). In addition, the nature of the trade-off relationship may be partially attributed to the uneven spacing of available pipe diameters. Tables 14.6 and 14.7 present the rehabilitation strategies for two model runs.

Now consider further constraining the model with a maximum permissible probability of system failure and a maximum amount of available funds for rehabilitation activities. Due to the mathematical complexities associated with evaluating the chance constraint, it is convenient to simply partition the set of possible rehabilitation strategies that make up the trade-off relationship between rehabilitation cost and probability of failure. For example, assume that available monetary resources for rehabilitation of this stormwater system equals $30,000 and the maximum permissible probability of failure equals 0.10.

The remaining feasible solutions represent the rehabilitation strategies that are available for implementation. Figure 14.7 illustrates the application of the maximum cost and probability of failure constraints. At this point, the design engineer must weigh the benefits of reducing the probability of failure against the additional cost of rehabilitation. For example, the probability of failure can be decreased from 0.0921 to 0.0754 for an increase in cost of $3,080. However, to further decrease the probability of failure to 0.0748 costs an additional $3,760.

A comparison of the rational formula and kinematic wave models is presented in Table 14.8, for 100 randomly selected storms, for overland flow into inlet structure 1. It shows clearly that the simpler rational formula model predicts almost twice the peak runoff rate.

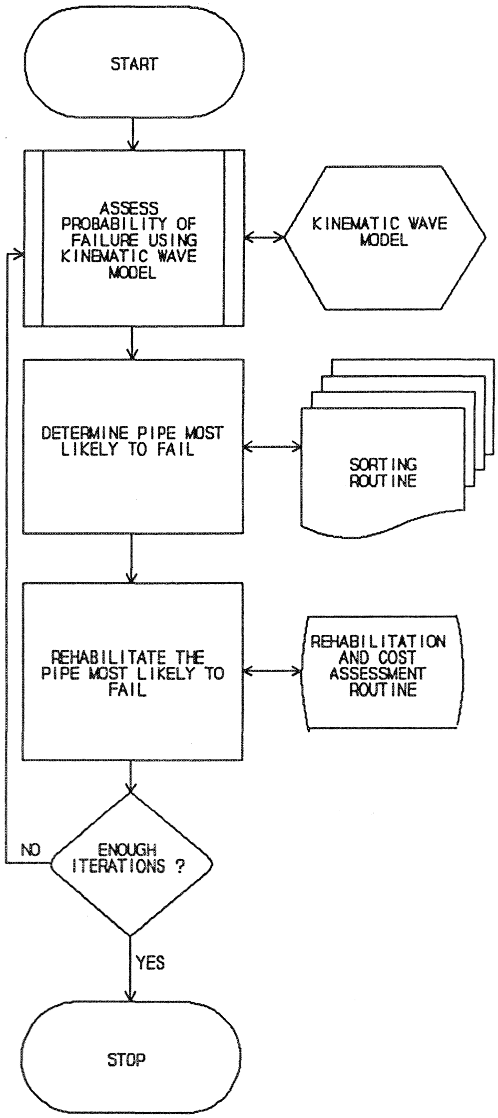

Figure 14.1
Heuristic solution algorithm

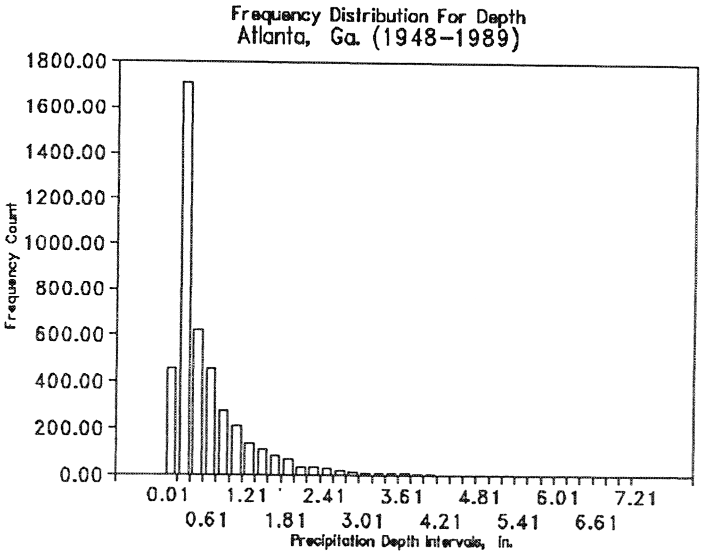

Figure 14.2
Rainfall depth frequency distribution

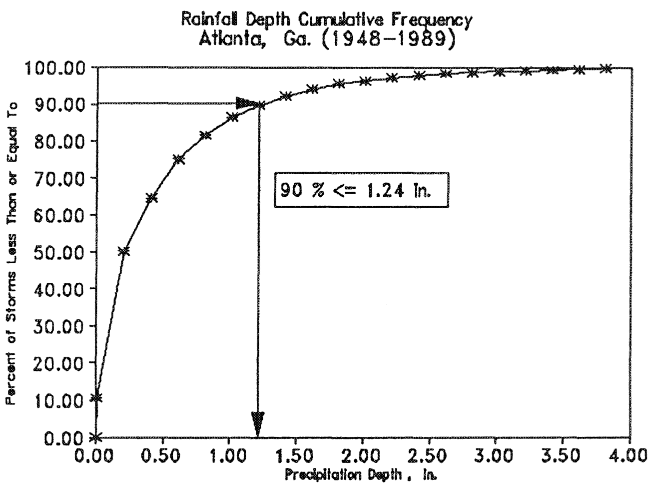

Figure 14.3
Rainfall depth cumulative distribution

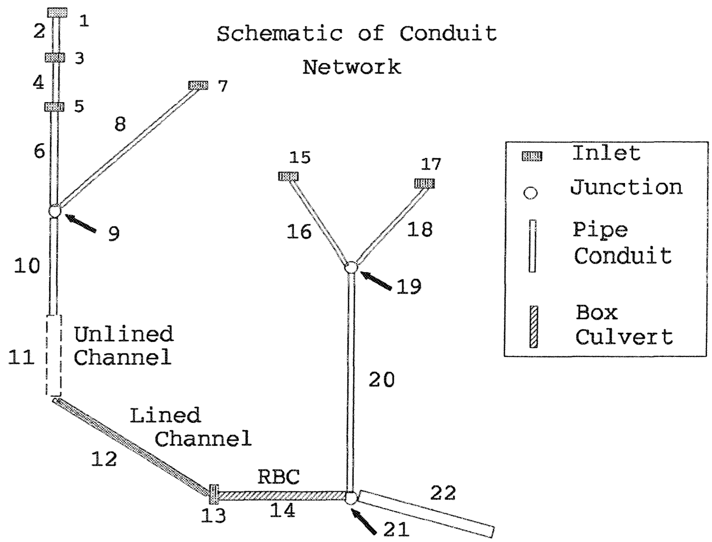

Figure 14.4
Atlanta stormwater drainage network

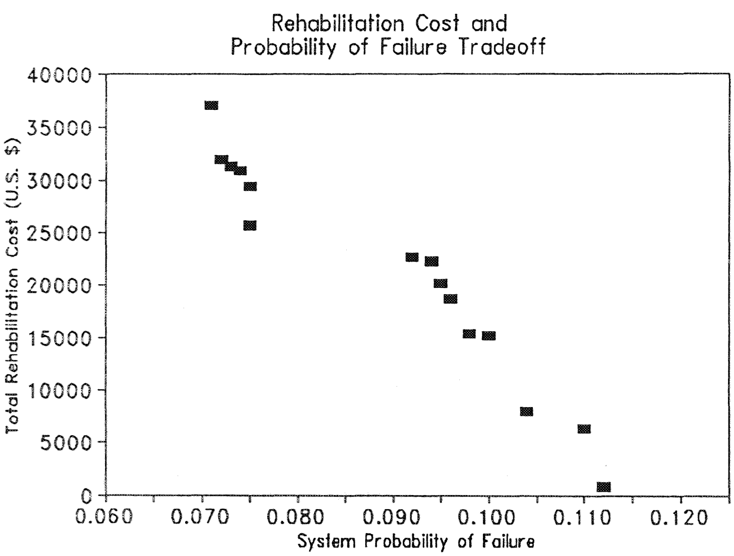

Figure 14.5
Rehabilitation cost and probability of failure tradeoff relationship.

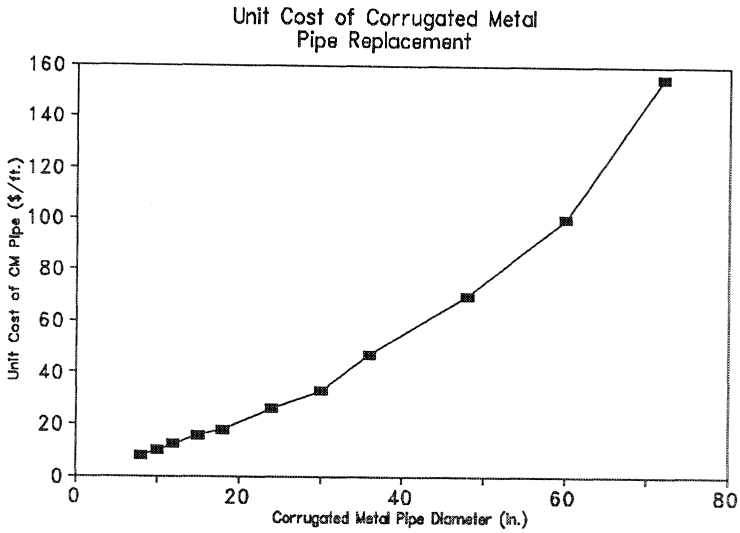

Figure 14.6
Unit cost of corrugated metal pipe replacement.

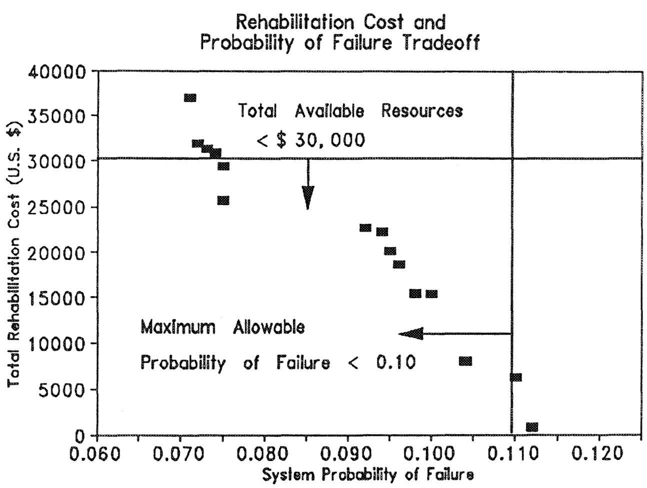

Figure 14.7
Feasible set of solutions with regard to available resources and maximum allowable probability of failure.

Table 14.1
NOAA Rainfall Station Description and Statistics of Storm Events, Atlanta, Georgia (1948-89)

NOAA Station No.	Description	Latitude / Longitude / Elevation	Length of Record
090451	Atlanta WSO AP, Fulton County; Hourly rainfall	33:39:00 / 84:26:00 / 1010 ft	42 years

Storm Event Variable	Mean	COV
No. of Storms[1] per year	103	0.13
Depth, inches	0.47	1.40
Intensity, in./hr	0.079	1.36
Duration, hours	6.79	1.15
Time Between Events , hours	83.70	1.07
Total No. of Storms[1]	4329	

[1] Note: Number of storms is based on a minimum interevent time of 6 hours, which yielded a coefficient of variation near 1.0 for time between events for the rainfall time series.

Table 14.2
Recorded Depths for Given Durations, Atlanta, GA (1948-1989)

Dur/hours	Dur/days	Amount	Storm	Date
1		2.61	14:00	7/29/1988
3		3.32	18:00	5/08/1969
6		3.92	15:00	5/08/1969
12		4.41	14:00	2/24/1961
24	1	5.67	13:00	2/24/1961
72	3	6.98	12:00	11/26/1948
168	7	11.52	07:00	2/18/1961
240	10	12.13	20:00	11/18/1948
336	14	12.51	18:00	11/16/1948
720	30	15.83	22:00	10/31/1948
1440	60	22.52	06:00	2/18/1961
2160	90	25.91	06:00	2/18/1961

Table 14.3
Number of Storms Exceeding Gumbel Extreme-Value T.P. No. 40 Depths and T.P. No. 25 Intensities, Atlanta (1948-1989)

Return Period (yrs)	T.P. No.40 24-Hour Depth, in.	T.P. No.25 One-Hour Intensity (in./hr)	Number of Historical[1] Storms Exceeding Given	
			Depth	Intensity
2	3.75	1.60	16	11
10	5.5	2.50	4	1
25	6.5	2.75	0	0
50	7.5	3.10	0	0
100	8.0	3.50	0	0

[1] Note: Total number of storms = 4329

Table 14.4
Original Stormwater Network Specifications

Pipe Segment	Type*	Manning's Roughness, n	Diameter (inches)	Length (feet)	Slope
2	RCP	0.015	10	40	0.024
4	CMP	0.024	10	50	0.008
6	RCP	0.015	15	180	0.018
8	CMP	0.024	8	170	0.013
10	RCP	0.015	12	400	0.031
16	CMP	0.024	8	210	0.021
18	RCP	0.015	8	250	0.019
20	CMP	0.024	18	350	0.009
22	CMP	0.024	24	220	0.021

*RCP = Reinforced Concrete Pipe
CMP = Corrugated Metal Pipe

Table 14.5
Unit Cost of Available Stormwater Pipes*

Corrugated Metal Pipe		Reinforced Concrete Pipe (Class 3)	
Pipe Size (inches)	Unit Cost ($/ft)	Pipe Size (inches)	Unit Cost ($/ft)
8	8	12	12.05
10	10.05	15	13.80
12	12.30	18	17.60
15	15.55	21	21.00
18	17.90	24	27.00
24	26.00	27	30.00
30	33.00	30	49.00
36	47.00	36	67.00
48	70.00	42	79.00
60	100.00	48	93.00
72	155.00	60	135.00

*Cost according to Means Building Construction Cost Data, 1992

Table 14.6
Typical Rehabilitation, Strategy I

Pipe Segment Rehabilitated	Size and Specification	Rehabilitation Cost ($)
4	18 in. CMP	895.00
10	18 in. RCP	7040.00
8	12 in. CMP	2091.00
22	36 in. CMP	10340.00
6	18 in. CMP	3222.00
16	10 in. CMP	2110.50
Total Rehabilitation Cost		= $25698.50
System Probability of Failure		= 0.07537

Table 14.7
Typical Rehabilitation, Strategy II

Pipe Segment Rehabilitated	Size and Specification	Rehabilitation Cost ($)
4	18 in. CMP	895.00
10	18 in. RCP	7040.00
8	12 in. CMP	2091.00
22	30 in. CMP	7260.00
6	18 in. CMP	3222.00
16	10 in. CMP	2110.50
Total Rehabilitation Cost	=	$22618.50
System Probability of Failure	=	0.09208

Table 14.8
Comparison of Rational Method and Kinematic Wave Routing[1], for Inlet Structure 1

Runoff Coefficient	0.4
Basin Size	5.3 acres
Mean Peak Runoff (Rational Method)	0.407 cfs
Mean Peak Runoff (Kinematic Wave Routing)	0.221 cfs

[1] Note: For 100 randomly selected storms, overland flow from catchment.

14.9 Summary and Conclusion

This chapter presents a chance constrained algorithm for evaluating possible rehabilitation strategies for stormwater drainage systems. The heuristic algorithm presented in this work implicitly evaluates the chance constraint governing the likelihood of system failure using Monte Carlo simulation in which the actual storm event is considered a random variable. This heuristic algorithm provides the practicing engineer with a tool for evaluating possible stormwater system rehabilitations in an environment in which system reliability and limited available funds must be considered simultaneously. To illustrate this model, an example stormwater network was presented using 42 years of storm event records from Atlanta, Georgia. The model results clearly illustrate the trade-off relationship that exists between rehabilitation cost and reliability. Similar results can aid engineers in developing "good" rehabilitation strategies for stormwater drainage systems subject to uncertain storm events.

List of Variables

A Overland flow cross-sectional area
A_c Channel flow cross-sectional area
α Kinematic wave overland flow parameter
α_c Kinematic wave channel flow parameter
B Channel top width
C_{ij} Cost of rehabilitating pipe segment i with rehabilitation alternative j
c_k Kinematic wave celerity
Δx Numerical model spatial increment
Δt Numerical model time increment
m Nonlinear kinematic wave overland flow parameter
m_c Nonlinear kinematic wave channel flow parameter
i Rainfall intensity
f Infiltration rate
n Manning's roughness coefficient
P Channel wetted perimeter
p_f Total probability of system failure
p_{fi} Probability of failure for segment i
q Flow per unit width
q_0 Lateral inflow
Q Overland flow
Q_c Channel flow
S Slope of overland flow plane
θ Kinematic wave speed parameter

t Time
x Coordinate axis of flow
X_{ij} Binary decision variable
y Flow depth

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