Evolutionary Optimization of Combined Sewer Overflow

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ABSTRACT

Model predictive control (MPC) is coupled with a real-coded Genetic Algorithm to predict a decision sequence that minimizes combined sewer overflow (CSO) volume for a 3-hour rainfall event over a hypothetical sewer system. Rainfall is transformed to overland runoff through the cell model which depicts each sewershed (draining to an overflow dropshaft) by two linear reservoirs in series, and water entering the interceptor is routed downstream to establish water levels at the dropshaft connections. A pumping rate at the most downstream end of the interceptor plus one sluice gate position for each dropshaft connection will be altered to produce the best control strategy. Resulting management scenarios disperse overflows differently throughout the sewer, but may yield similar overflow volumes. This paper describes the simulation approach taken and displays the overflow distribution for favorable control sequences.

INTRODUCTION

Combined sewers, such as those found in the Chicago region, are susceptible to overflows during severe rainfall events when runoff from urban sewersheds enters interceptor conduits through sluice gate connections. This runoff combines with sanitary sewage and may overwhelm the interceptor capacity. In an effort to minimize overflows that occur when flows exceed the sewer capacity, a genetic algorithm has been applied to a generalized hydrologic-hydraulic model to generate optimal management scenarios for a hypothetical sewer network.

Recent advances in the real-time control of sewer overflows include work by Darsono and Labadie (2007) to minimize overflow volumes and maximize flow to a wastewater treatment plant. A volume-based overflow control strategy is determined to be preferable to a pollution- or emission- based control. Pleau et al. (2005) use a multi-objective non-linear programming algorithm to minimize overflows (among other goals) in the Quebec sewer system by computing water levels for a control horizon discretized into 5-minute intervals. Generalized reduced gradient search has been applied to reduce combined sewer overflows by Cembrano et al. (2004); water levels are predicted for a 30-minute horizon at 5-minute control intervals. Rauch and Harremoes (1999) apply model predictive control in conjunction with a genetic algorithm to maximize the mean dissolved oxygen concentration below an urban wastewater system.

Application of model-based predictive control for real-time decision support has also been applied to the problem of aircraft arrival scheduling; Hu and Chen (2005) minimize the airborne delay of aircraft approaching a runway. Lee et al. (2005) utilize rolling horizon control and a binary coded genetic algorithm to minimize vehicle delays in real-time traffic signal control. Naeem et al. (2005) apply a genetic algorithm and model predictive control to the operation of an autonomous underwater vehicle. Further investigation of genetic algorithms used for predictive control has indicated that population initializing and sizing should be altered slightly for the specific predictive application (Onnen et al., 1997). A real-coded GA is appropriate for the CSO application addressed in this paper because it eliminates the need for the control variables to be converted to binary coding and enables the problem to be optimized without restructuring the physical formulation.

METHODS

The MPC formulation involves minimizing the predicted volume of overflow, V, calculated at sequential 15-minute time increments Δt, to be evaluated out to time horizon $t + (\Delta t \times N)$ based on system information available at time t.

$$\text{minimize} \sum_{k=1}^{N} \left\{ V\big(t + (k \times \Delta t)\big) \middle| t \right\} \tag{1}$$

The variable t indicates the current time, and N is the number of time intervals in the prediction horizon. The value of N is set to 8 to designate a 2-hour prediction horizon divided into 15-minute intervals. The volume depends on the values of the current and future control signals which consist of one pumping rate and three sluice gate positions and are designated by the vector Y in Eqn. 2.

$$\sum_{k=0}^{N-1} \left\{ Y\big(t + (k \times \Delta t)\big) \middle| t \right\} \tag{2}$$

The summation indicates the inclusion of all control signals within the prediction window. At time $t+1$, the control signal $Y(t)$ is implemented in the hydrologic-hydraulic model, and the computation is repeated with the prediction horizon (k) moving forward one interval. The interval t is advanced with k at Δt until no additional overflows are predicted within the window $t + (\Delta t \times N)$.

Within the MPC algorithm for the hydrologic-hydraulic system, the cell model introduced by Diskin et al. (1984), and further utilized by Karnieli et al. (1994) and Ostfeld and Pries (2003) is utilized to route excess rainfall water overland to each connecting structure. The model convolutes rainfall in accordance with a unit hydrograph U that has been created for the two linear reservoirs in series (Dooge, 1973) that represent each sewershed.

$$U(t) = \frac{e^{-t/K_1} - e^{-t/K_2}}{K_1 - K_2} \tag{3}$$

The variables K_1 and K_2 are the storage coefficients of each reservoir (in units of 1 over time); in this case $K_2 = 0.1K_1$ and K_1 is proportional to the sewershed area (A_c)

and an overall mean reservoir coefficient (A_{KC}) that can be used for calibration during implementation in an actual sewershed. The mean sewershed area is given as A_m.

$$K_1 = A_{KC}\left[\frac{A_c}{A_m}\right]^{0.5} \tag{4}$$

The hydrograph unit U is the inverse of time. The resulting hydrograph flows (Q_n) are generated for each sewershed through convolution of the linear system, where M is the number of input rainfall pulses (P_m) and n is the current time step.

$$Q_n = \sum_{m=1}^{n\leq M} P_m U_{n-m+1} \tag{5}$$

The precipitation P is a volume. Flows from each sewershed into the interceptor are calculated by equations derived by Swamee (1992) for flow under a sluice gate. Flow can occur either from the connecting structure to the tunnel or from the tunnel to the connecting structure. If the sluice gate is not submerged, the flow can be calculated by Eqn. 6

$$Q = 0.864ab\sqrt{gh_0}\left(\frac{h_0 - a}{h_0 + 15a}\right)^{0.072} \tag{6}$$

where a represents the height of the sluice-gate opening, b is the width of the gate opening, h_0 is the upstream water depth (the higher of the tunnel and the connecting structure water surface elevation), and g is gravitational acceleration. The same variables hold for the case of submerged flow in Eqn. 7

$$Q = 0.864ab\sqrt{gh_0}\left(\frac{h_0 - a}{h_0 + 15a}\right)^{0.072}(h_0 - h_2)^{0.7}\left[0.32\left[0.81h_2\left(\frac{h_2}{a}\right)^{0.72} - h_0\right]^{0.7} + (h_0 - h_2)^{0.7}\right]^{-1} \tag{7}$$

where h_2 is the tailwater depth (the lower of the connecting structure water surface elevation or the tunnel water elevation at that point.) Water is permitted to flow only when h_0 is larger than h_2. Revised sluice gate calculations may be implemented in the final model.

Currently, hydraulic routing computations are simplified by assuming a level pool solution (LMNO Engineering, 2008) for interceptor water level. This results in Eqn. 8, where the volume (V) is calculated from the sluice gate equations and the time step, and the distance along the tunnel wall to which the water rises, S, is translated to a water surface elevation. The slope of the interceptor Φ is 0.0015, and r is the pipe radius.

$$V = \pi r^2\left(S + \frac{r}{\tan \emptyset}\right) \tag{8}$$

Once water elevations are established throughout the system, the elevations in the interceptor at the connecting structures can be compared with the water surface elevations within the connecting structures. The sluice gate equations (6 and 7) can then be applied to determine the direction and the magnitude of flow.

The MPC algorithm implemented for this study is similar to the algorithms used by Onnen et al. (1997) and Naeem et al. (2005) and is illustrated in Figure 1. Chromosome genes represent percentages of sluice gate closures or the percent of maximum pumping rate and are coded between 0 and 1 and rounded to one decimal place. After initialization and mutation, the gene values are set to 0 or 1 if they are negative or greater than 1, respectively. Each gene can take one of 11 possible values.

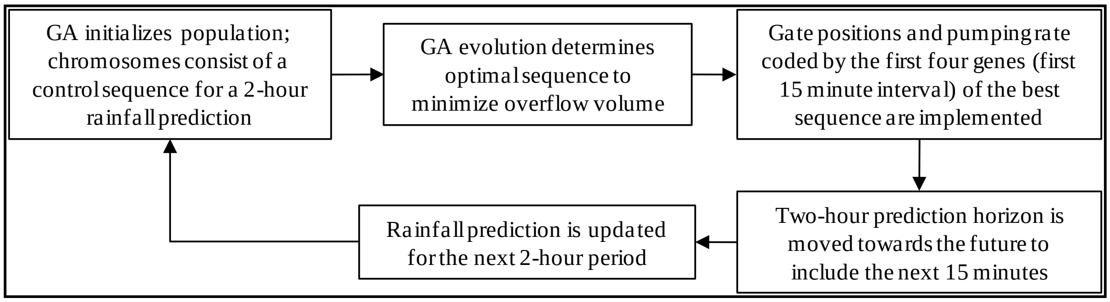

Figure 1: MPC Schematic

The genetic algorithm initializes a population of chromosomes composed of genes, and iteratively applies the operators of selection, crossover, and mutation to produce chromosomes of higher fitness. Real-coded genes increase the algorithm search space, and as a result, mutation rates and/or population sizes should be increased to ensure adequate search (Tate and Smith, 1993). Wright (1991) also supports higher mutation rates. Herrera et al. (1998) summarize numerous methods for real coded GA crossover and mutation; they resolve that non-uniform mutation (NUM) appears to yield fine tuning and the best results in later stages of the GA. Chen (2003) and Chang and Chen (1998) resolve that in terms of crossover, blended crossover (BLX-0.5) exhibits the best performance.

The GA used in this study uses binary tournament selection with replacement where the individual with maximum fitness (minimum overflow volume) is chosen. BLX-0.5 crossover is implemented as described by Herrera et al. (1998) and Eshelman et al. (1993). This method requires the definition of two limits and one integer.

$$c_{min} = \min(c_i^1, c_i^2), c_{max} = \max(c_i^1, c_i^2), I = c_{max} - c_{min} \tag{9}$$

Where the c values represent the gene values from the parent individuals at the i^{th} location. The value of each of two new genes, h_i, is computed to be a random number on the closed interval given in Eqn. 10.

$$[c_{min} - I \cdot \alpha, c_{max} + I \cdot \alpha] \tag{10}$$

To enable local search, the GA used in this study also employs non-uniform mutation based on a mutation size that decreases as the number of generations increase (Herrera et al. 1998; Michalewicz 1992). For this operator applied in generation t, where g_{max} is the maximum number of generations, the value of the mutated gene c_i' is given in Eqn. 11.

$$c_i' = \begin{cases} c_i + \Delta(t, b_i - c_i) \; if \; \tau = 0 \\ c_i - \Delta(t, c_i - a_i) \; if \; \tau = 1 \end{cases} \tag{11}$$

where τ is a random number that can be either 1 or 0 with 50% probability, b is the closed domain to which the mutated gene is constrained, and Δ is the function in Eqn. 12.

$$\Delta(t, y) = y\left(1 - r^{\left(1 - \frac{t}{gmax}\right)^b}\right) \tag{12}$$

where r is a random number from the closed interval 0 to 1 and b is a parameter taken to be 5 in accordance with the value applied by Herrera et al. (1995). For all steps, the maximum number of generations is set to 100; this number must be specified when using non-uniform mutation.

Three approaches are compared for population initialization at each new time interval. The first involves randomly initializing every chromosome (by generating 32 new genes with values between 0 and 1). The other methods constitute identifying the best chromosome from the last time window, and shifting the genes 4 places to the left to retain system knowledge gained in the last interval. Four new randomly generated values are placed at the end of the string to simulate decisions for the next 15 minutes of rainfall. The gene shifting procedure is shown in Figure 2.

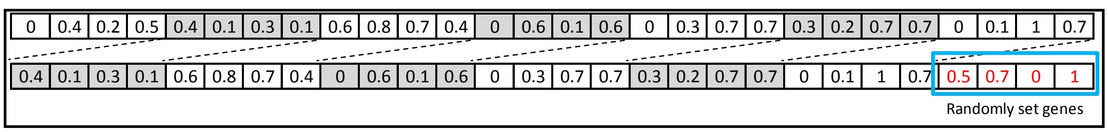

Figure 2: Gene Shifting Method

The second method reinitializes the entire new population with the chromosome of shifted genes (as a result the population only differs by the last four genes of each chromosome). The third strategy entails reinitializing only two members in the next population with these genes. Two chromosomes in the initial GA population for the next time window are replaced with the shifted values, while the remaining chromosomes are randomly initialized.

CASE STUDY

The combined generalized hydraulic model, MPC algorithm, and GA system is demonstrated using a small test case that is roughly based on a portion of the Chicago Tunnel and Reservoir Plan (TARP) system. Case study results are analyzed in order to facilitate development of the decision sequence optimization system as well as provide insight as to regions of the hydrologic-hydraulic system where more accurate modeling is needed.

The coupled hydrologic-hydraulic model used to simulate the rainfall to runoff process is depicted in Figure 3. The system consists of three sewersheds, represented by squares 1 through 3 that are connected through connecting structures (nodes 1 through 3) to conduits 1 through 3 that convey water to a downstream treatment plant and pumping station; arrows designate the flow direction.

The conduit diameters (D), upstream elevations (El_u), downstream elevations (El_d) and lengths (L) are included in Figure 3. Sluice gates that restrict water flow to and from the conduits are located in each connecting structure. The area of watershed 1 is 161 hectares, the area of watershed 2 is 243 hectares, and the area of watershed 3 is 81 hectares. The flow from each of the three sewersheds that enters the conduits is routed downstream to establish water levels throughout the sewer. Water levels at each connecting structure determine whether an overflow will occur. Overflows can occur in the following three ways, volume from each of which is given equal weight within the optimization.

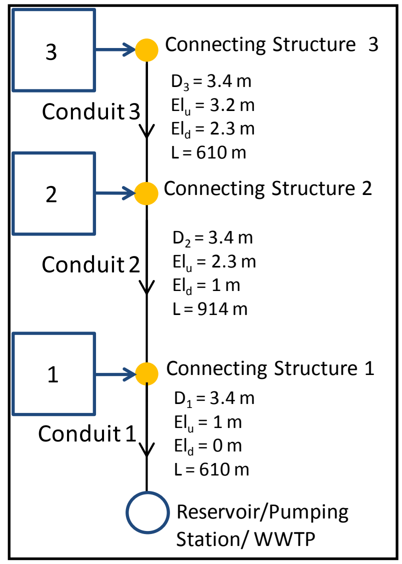

Figure 3: Hypothetical System

1) Local CSO: Water can overflow the connecting structure if the flow in from overland is greater than flow permitted to leave through the sluice gate to the conduit.
2) Pump Station CSO: If the pumping station lifts more water than the treatment plant capacity, water must overflow as opposed to entering the treatment plant.
3) Global CSO: Flows into the reservoir may be greater than the pumping capacity, and water can back up along the interceptor. When the elevation of water in the interceptor is greater than the water level in any of the connecting structures, flow exits the conduit into the connecting structure through the sluice gate, constituting an overflow.

The minimum cumulative volume of sewer overflow events throughout a 3-hour storm (and resulting 5-hour overflow duration) is sought for the watershed-interceptor system. This volume will be achieved through the optimal sequence of management decisions (consisting of a single pumping rate and three sluice gate positions at multiple time steps) derived using model predictive control. Three random number generator seeds, constituting trials 1 through 3, are utilized to provide an overview of possible sequences.

In the results presented, the algorithm is implemented assuming the rainfall is known for the 3-hour storm (displayed in Table 1) and no changes in the prediction occur.

Table 1: Simulated Rainfall

15 minute interval	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Rainfall (cm/hr)	0	1.3	1.3	1.3	1.3	2.5	2.5	2.5	2.5	1	1	1	1	0	0	0	0	0	0

The 0 cm/hr rainfall input is continued until all overflows have subsided.

Each gene is represented by one integer (that takes a value from 0 to 10) and four genes represent the system at each 15-minute interval. For a 2-hour prediction horizon, the chromosome length is determined in Eqn. 13.

$$4\left(\frac{variables}{interval}\right) \times 2(hours) \times 60\left(\frac{minutes}{hour}\right) \Big/ 15\left(\frac{minutes}{interval}\right) \qquad (13)$$

Eqn. 13 indicates a total of 32 genes per chromosome. The population size will be set to the chromosome length times a constant value of 8 for a value of 256, as suggested by Onnen et al. (1997.) This population size may be reduced when a more physics-based hydrologic-hydraulic model is implemented in order to allow all chromosomes to be evaluated within 15 minutes.

RESULTS AND DISCUSSION

Initially, a crossover probability of 0.5 is used for single point real crossover; nonuniform mutation is used for 100 generations and a mutation probability of 0.01. Figure 4 demonstrates the spatial and temporal overflow distribution when the GA initializes a generation and does not perform further operations for the optimization routine for the 20 interval (5-hour) decision sequence. Only one value of the random seed is used.

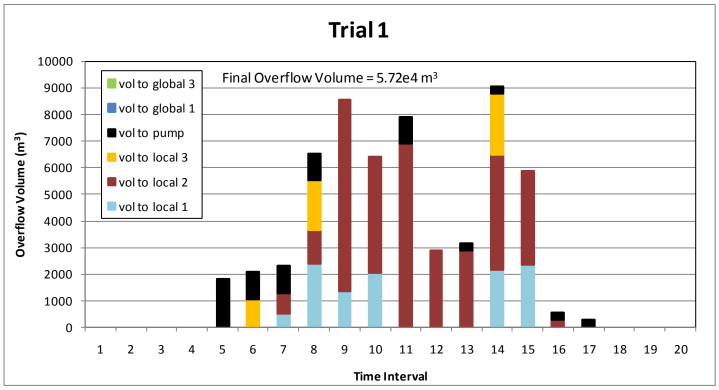

Figure 4: Implemented Sequence for Trial 1

The cumulative overflow volume is 5.72e4 cubic meters. The overflow distribution demonstrates that the largest volume is partitioned as a local overflow out of dropshaft 2 (at the sewershed with the largest drainage area.) CSOs at the pump station also exhibit a large volume, indicating that the pumping rate is increased substantially above the treatment plant capacity.

Initial GA Results

The GA is utilized to transform chromosomes over 100 generations, and three different random seeds (trials) are utilized. Figures 5 through 7 show the implemented sequences for each trial produced by the lowest fitness chromosomes in the final generation at each time increment.

Results show that decisions made at time intervals when very little rainfall has entered and/or remains in the system do not significantly impact the total overflow volume. Many different decision sequences, which differ in the decisions made during early and late time intervals, demonstrate equivalently optimal fitness. For a 2-hour window starting at time step 1, the only overflow that is predicted to occur is at the eighth time step at dropshaft 2. All chromosomes for all seeds predict this local overflow; but the series of gate closures and pumping rates previous to this interval differ.

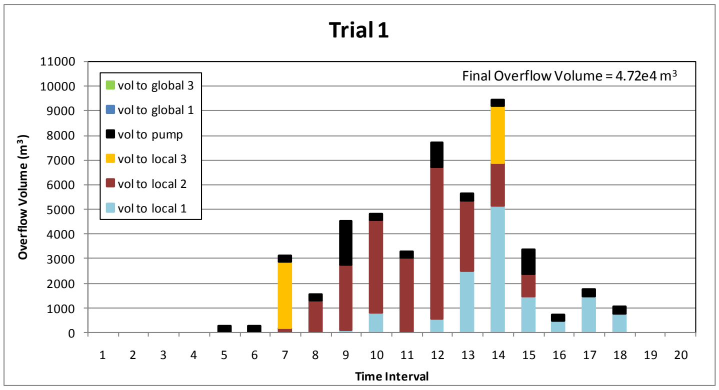

Figure 5: Implemented Sequence for Trial 1

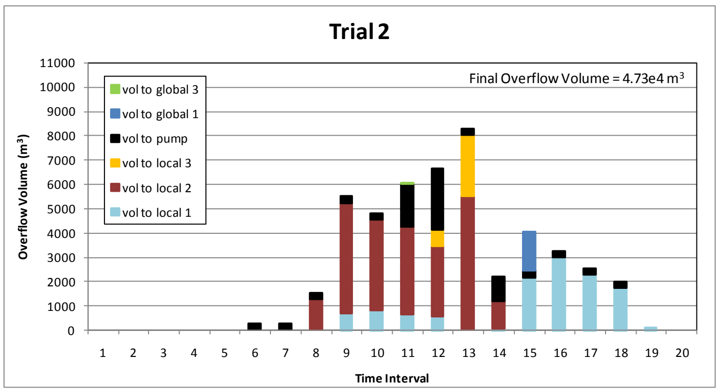

Figure 6: Implemented Sequence for Trial 2

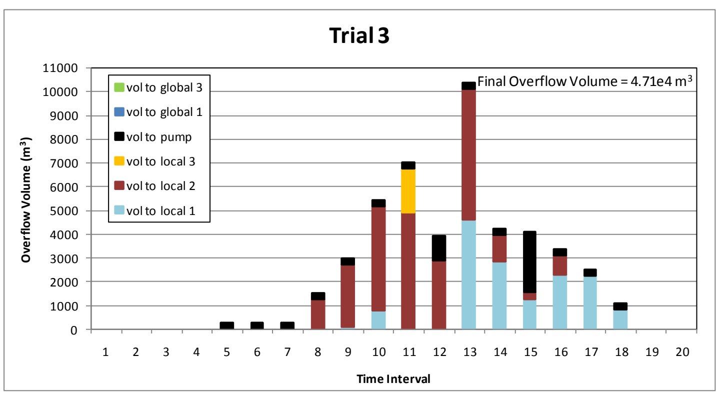

Figure 7: Implemented Sequence for Trial 3

The strategies proposed by the different seeds differ significantly; however local overflows at connecting structure 2 dominate for early time intervals for all seeds and a large number of local overflows at dropshaft 1 occur later in the storm. Local overflows at structure 1 indicate that sluice gate 1 is closed to prohibit global overflows that may be caused at that location because once more water enters the sewer, connecting structure 1 will be the first affected by backups.

The population size used in this algorithm is fixed, and a high mutation rate is necessary to expand the breadth of the search at least for early generations. The mutation rate is increased to 0.05 to aid in the search for good solutions for a large real-coded alphabet, and elitism is introduced. BLX-0 and BLX-0.5 crossover are introduced, and although they have no effect on their own, introduction of chromosome shifting significantly effects the overflow volumes obtained.

Results for Revised GA Parameters

Introduction of the gene shifting strategy for population initialization significantly reduces the overflow volumes, and leads to a convergence among spatial and temporal overflow partitioning for all three trials. At the same time period for all three trials, the volume is partitioned to the same local or global overflows. The average volume generated over the storm duration decreases from 4.72e4 cubic meters to 4.60e4 cubic meters. The improved performance obtained by gene shifting may be amplified by the deterministic rainfall assumed in this problem. Further work will implement more realistic, changing precipitation forecasts necessary to validate the superiority of the gene shifting strategy.

The distribution of overflows throughout the system is shown in Figures 8 through 10 for population initialization with two chromosomes with shifted genes. The predictions (final chromosomes) for intervals beginning at time steps 1 through 4 and from steps 18 though 21 differ the most due to lack of water in the system.

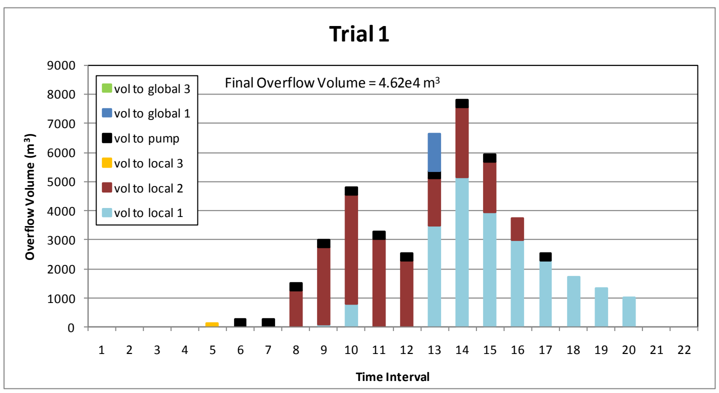

Figure 8: Implemented Sequence for Trial 1

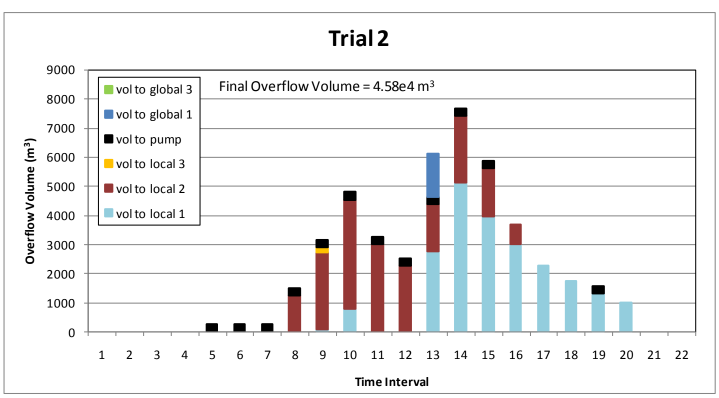

Figure 9: Implemented Sequence for Trial 2

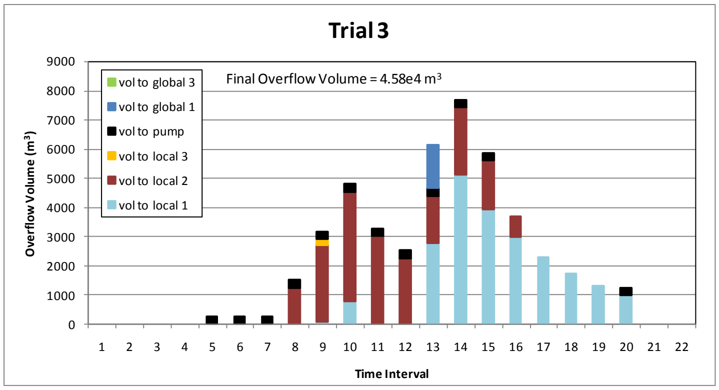

Figure 10: Implemented Sequence for Trial 3

The implemented decision variables demonstrate that that the best management strategy is to keep the pump on at the capacity closest to the treatment plant rate throughout the storm event rather than pumping at higher rates at inconsistent intervals. All trials also indicate that sluice gate 2 should be fully open for the middle intervals of the rainfall, and towards the end of the rainfall, sluice gate 1 should be fully closed and sluice gate 3 should be partially closed while water from sewershed 2 is pumped out of the system. The three strategies extend the number of intervals for which overflows occur from 19 to 20. For all trials, one global overflow occurs at time interval 13, and no overflows occur after interval 20.

CONCLUSIONS AND FUTURE WORK

This study develops a real-time GA-based control system for managing CSOs. The system employs a real coded genetic algorithm to develop management strategies that most effectively reduce overflow volume over a 5-hour window using 15-minute control intervals and a 2-hour planning horizon. At each control interval, the system re-evaluates the optimal 2-hour decision sequence to account for changing precipitation conditions. The system is implemented in a case study roughly based on a portion of the Chicago TARP system.

The decision sequences that produce the lowest CSO volume are obtained when the genes for the best chromosome in the previous time window are shifted for initialization in the next window; this method of initialization propagates knowledge of the best management strategy to the next generation. Additionally, this method of population initialization allows decision sequences derived from different random seeds to converge to similar partitioning of overflow volume for the entire 5-hour optimization period. It may prove beneficial to initialize only two members of the subsequent population with the shifted genes, allowing the remainder of the chromosomes to be randomly generated, thus enlarging the search space. This method may also save computational effort; fewer GA generations may be required to reach a good solution when genes shifted from the previous time interval are utilized.

Future work will include further evaluation of the genetic algorithm. New strategies of population initializing at each time window should incorporate evaluation of the necessity of rerunning the algorithm at every 15 minute interval for low changes in rainfall rate. A threshold change in rainfall rate may exist below which the decision sequence remains consistent for the initial steps of a new time window. The effects of population size on minimum fitness and the types of chromosomes of minimum fitness should be further examined; high mutation rates should be evaluated as a substitute for increases in population size.

Different weights could be assigned to the location and timing of overflows. This extension would be valuable for possible use within a water quality model in which portions of the receiving waterway downstream of certain sewersheds are more sensitive to overflow contamination than others. The analysis may restructure the spatial and temporal patterns observed for the equivalent weighting presented.

The insight into GA parameters and physical characteristics for this case study will be applied to a more physics-based model, in which interceptor hydraulics will be based on the methodology proposed by Hoy (2005). A hydraulic performance graph (HPG) and a volumetric performance graph (VPG) will be established for each conduit. The HPG ensures conservation of momentum for the reach and is a collection of the backwater profiles of the reach created through the gradually varied flow equation (Chow, 1959).

$$\frac{dh}{dx} = \frac{S_0 - S_f}{1 - F^2} \tag{14}$$

The HPG has been used to analyze open channel stage-discharge relations (Schmidt, 2002) and applied to unsteady flow routing by Gonzalez-Castro (2000). The VPG introduced by Hoy (2005) describes the volume stored in the reach for each flow condition described by the HPG, and ensures conservation of mass for the reach.

$$\frac{\partial A}{\partial t} + \frac{\partial Q}{\partial x} = q_{lateral} \tag{15}$$

The change in flow area with respect to time plus the change in flow rate with respect to distance is equal to any lateral inflows to the reach. All water entering the conduit system is immediately transferred to the downstream reservoir and from there is routed back upstream to establish conduit water level in accordance with work done by Oberg et al. (2001). The HPG and VPG files are created offline for a range of flow rates and downstream boundary conditions for the sub-conduits through tools scripted in $C{+}{+}$ (Oberg, 2008). The graphs will be used for interpolation during the MPC algorithm.

At each time step, the HPG is used to find the upstream water surface elevation for each conduit given the average flowrate and the downstream water surface elevation. The VPG is used to determine the storage in each reach for the current time step, using the same inputs utilized for the HPG. Optimization is performed to find the minimum least squares solution that equates the change in storage with space to the change in storage with time, that is, to minimize the difference: $\Delta S_{time} - \Delta S_{space}$ for each conduit. The solution will provide flow rates for each sub-conduit which can then be utilized to find upstream water surface elevations throughout the system.

The finalized coupled hydrologic-hydraulic model will be used to evaluate the sensitivity of local, global, or pump station overflows to system management. The procedure will eventually be extended to the Metropolitan Water Reclamation

District of Greater Chicago's (MWRDGC) Tunnel and Reservoir Plan (TARP). The system will be utilized with real-time precipitation updates, and calibrated to CSO data provided by the MWRDGC.

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