Enhancing the Performance of Multiobjective Evolutionary Algorithms for Sanitary Sewer Rehabilitation Problems

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Abstract

The application of evolutionary algorithms (EA) to optimize the rehabilitation of existing sanitary sewer systems is challenging because sewer network are complex and requires computationally demanding hydraulic models to obtain accurate representation of the system. Additionally, the large number of conduits in a typical sewer network makes it difficult to find the near optimal solutions within a few number of iterations of optimization algorithms. To address this problem, there is a need for EA operators that requires fewer number of function evaluations and converge to near optimum solutions faster. A new operator is explored to enhance the performance of multiobjective evolutionary algorithms (MOEA) for sanitary sewer rehabilitation optimization problem. The proposed operator is based on the nondominated sorting evolutionary strategies (NSES) which combines the Pareto optimality of the nondominated sorting genetic algorithm (NSGA II) with evolution strategies (ES). The operator is based on a graph of topologically connected conduits so as to guide the search toward known SSOs locations, thereby speeding up the convergence time. The MOEA is designed to find solutions that address two conflicting objectives: maximize sanitary sewer overflow (SSO) reduction and minimize rehabilitation cost. The hydraulics of the network is modeled using the EPA storm water management model (SWMM). The proposed operator is applied to an existing sewer network in the eastern San Antonio water system (SAWS) network.

INTRODUCTION

Sanitary sewer systems are critical infrastructures and are design to convey residential, commercial and industrial wastewater to treatment facilities. Insufficient capacity or excess flow from rain derived infiltration and inflow (RDII) could result in unintentional discharge of the sewage from the network. This discharge is referred to as sanitary sewer overflows (SSOs). Current rehabilitation approaches to resolving SSOs typically involves retrofitting existing sewer with larger diameters conduits to enhance flow capacity. One of the drawbacks of pipe capacity enhancement is that changes to one segment in a network can result in further hydraulic loading on other parts of the network, thereby causing more SSOs elsewhere in the system. Because of budgetary constraints, it is infeasible to upgrade the entire system at once. Optimization algorithms can be used to determine the best rehabilitation plans that maximize SSO reduction and minimize rehabilitation costs. Combining optimization algorithms with hydraulic models can identify good solutions with respect to hydraulic efficiency of the entire network and costs.

Although optimization algorithms have been used in combined sewer systems, the literature about their use in rehabilitation of sanitary sewer problems is more limited. Moreover, most of the previous studies have applied optimization techniques in the design of new wastewater collection systems but not in a rehabilitation stage. For instance, Wright et al. (2001) coupled a long-term hydrologic simulation model with a Genetic Algorithm (GA) to identify least cost design solutions, as well as to identify non-inferior set of solutions to characterize the tradeoff between cost and reliability of the system. Liang et al. (2004) applied GA and Tabu Search (TS) (Liang et al., 2004) for designing gravity wastewater collection systems. An adaptive rule and dynamic search strategy was developed to ensure that only solutions that don't violate the constraints can be generated. The adaptive rule "fixes" chromosomes that violate the diameter progression constraint by replacing violating genes. The performance of GA and TS were compared to conventional design, both optimization techniques finding significant reduction in construction costs for a case study of 6.2 km of wastewater collection system. Sun et al. (2011) proposed a GA based framework for the optimal design of storm sewer network that minimize the design cost and expected flood damage to determine the optimal diameters and slopes of the pipe networks. Rathnayake and Tanyimboh (2015) implemented a multiobjective evolutionary optimization for control of combined sewer overflows (CSO) that consider unsteady sewer flow, the pollution load to receiving water bodies and the associated treatment cost of the excess RDII. The optimization problem was used to explore the tradeoffs between CSO from storm overflow tanks and the treatment costs of the fraction of the excess water that reached the treatment facility. Yazdi et al. (2015) proposed a risk-based optimization approach that combined the Monte Carlo simulation, a MOEA and hydrodynamic model to determine the solutions that represent compromise between the objectives of pipe and pump renewal costs and expected overflow reduction capacity in 44 ha storm sewer network in Seoul, South Korea.

All the aforementioned studies applied GA-based evolutionary algorithms that implements crossover and mutation operators to facilitate the exploration and exploitation of the search space to find near optima solutions. The application of the crossover operator in sewer system optimization problem however, could result in solutions that do not reflect the hydraulic flow path of wastewater in the network. For example, during crossover, the combination of two parents' genes may result in offspring vectors that specify a new solution at a distant location from the original solution causing genetic drift whereby a large part of the search space is not explored. Additionally, the application of EA to sewer rehabilitation problem is computationally demanding because EA require a large number of functional evaluations of complex hydraulic models to solve the SSO problems.

To tackle these challenges, an optimization approach is needed that is able to find near optima solution with fewer functional evaluation of the hydraulic models than the traditional GA-based algorithms. Previous studies have sought to address similar problems in drinking water distribution systems. Zechman and Ranjithan (2009) implemented an Evolutionary Strategies (ES) that uses only mutation operator as the evolutionary parameter to search for contamination source in a virtual city drinking water system. Kanta et al. (2012) built on this approach to develop the nondominated sorting evolutionary strategy (NSES) that combined the speed of evolutionary strategies with the Pareto optimality of NSGAII. In both of these studies, the probabilistic mutation operators are based on a graph of the connected pipes in a network where the mean of the curve is the location of the current pipe.

In this study, a specialized operator is combined with the NSES to guide the search of the multiobjective EA toward known SSO locations in the sewer system to enhance the convergence time of the optimization. The simulation-optimization framework is linked with the Environmental Protection Agency (EPA) Storm Water Management Model (SWMM) to perform hydraulic routing and to calculate the number of flooded nodes in the system during a design storm event. The methodology is tested in a sewershed of the San Antonio Water Systems (SAWS) sewer network, located in San Antonio, Texas.

CASE STUDY DESCRIPTION

The case study is the E-07-15 sewershed inside the San Antonio Water Systems (SAWS) eastern sewer network with an area equal to 20.4 square miles, which represents 3% of the entire wastewater network. The sewershed is composed of 3,304 conduits connected via 3,155 manholes to form a network that is 160.8 miles long and service 36,000 inhabitants. The sewershed is monitored for flow at six flow meters which enable its delineation to six metershed (Figure 1). Approximately 70% of the population resides in the three northern metersheds, which is comprised primarily of residential land use. The central and two southern metersheds contain approximately 30% of the total population and are primarily commercial properties. Under existing condition, 23 nodes overflowed in the network during a 5 year – 6 hour design storm (106.7 mm) which are shown in Figure 1as red circles.

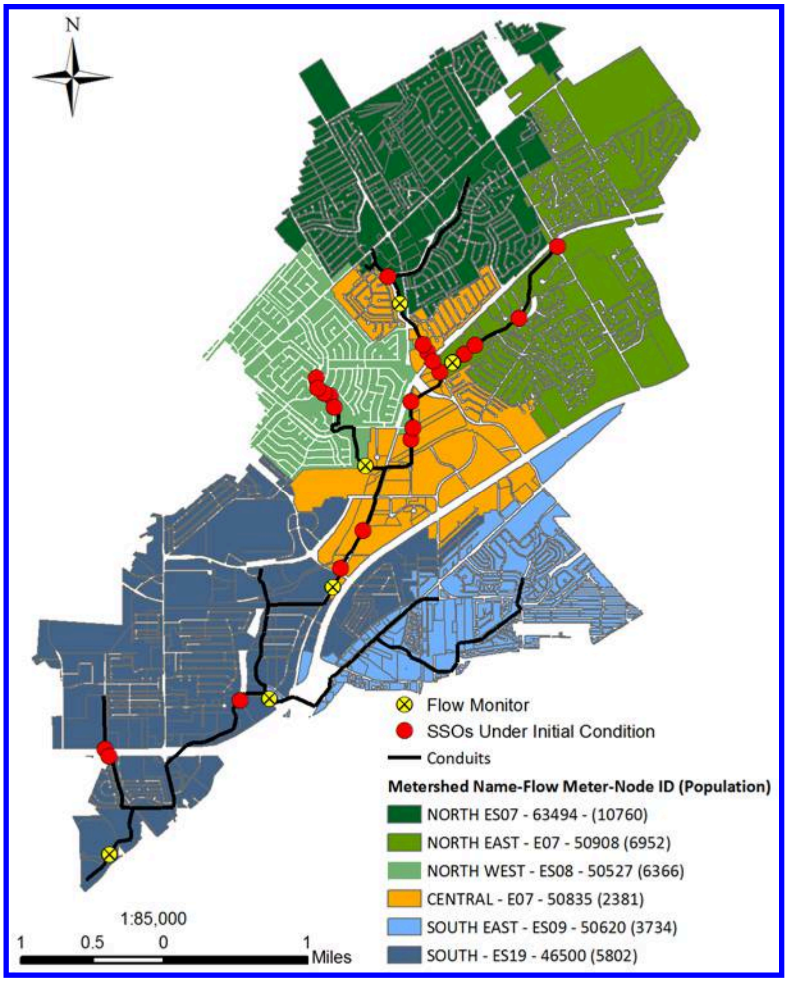

Figure 1- Case study showing metersheds, flow monitors and location and volume of overflows.

PROBLEM FORMULATION

Objective Functions

The SSO optimization problem is posed in this study to explore the tradeoffs between two conflicting objectives: maximization of SSO reduction and minimization of rehabilitation costs. The multiobjective problem is represented mathematically as follows:

$$\text{minimize } f_1 = \left(\sum_{k=0}^{np} C_{D_k} \times L_k + \sum_{n=0}^{nm} C_n \right) + (1 + y)$$

$$\text{maximize } f_2 = 1 - \left(\sum_{j=0}^{N} \sum_{t=0}^{T} SSO_j^t \Big/ \sum SSO_{Curr} \right)$$

Subject to the following:

$D_k \epsilon \{d\}; \quad k = 1,2, \dots, np$

$D_k \leq D_{k+1}$

$np \leq \emptyset$

where, np is the number of rehabilitated pipes; C_{D_k} is the unit cost per length of pipe (k) with diameter with D_k and length L_k; C_{D_k} include Post and Pre-Construction sanitary sewer main television inspection, trench excavation cost and hot mix asphaltic concrete pavement replacement; C_n is the unit cost of replacing a manhole; nm is the total number of nodes (manholes) in the network that must be replaced when np pipes are rehabilitated; y is the fraction of unit costs that represent the cost of mobilization of personnel and equipment, right of way and by pass pumping; $\emptyset$ is the user defined maximum number of replacement segments; N is the total number of nodes in the network; T is the total simulation time. SSO_j^t is a binary variable (0 or 1) that represents if an overflow occurs in the node j at time t and SSO_{Curr} is the number of overflows that occurred under existing condition.

Decision Variables

The decision variables is composed of three parts; the first is the binary genes that determine whether the segment will be replaced; the second is an integer number representing the node immediately upstream of the first conduit in the replaced segment and the last is the commercial diameter increase from the existing sewer pipe diameter. As typical in ES, each gene is represented by a normal parameter, α_k which is the primary decision variables and an endogenous strategy parameter, σ_k which is used to mutate the individuals. The strategy parameters have to be carefully defined in order to maintain a balance between exploration and exploitation during the search. In the beginning of the evolutionary process, the search must avoid premature convergence by exploring the search space. Towards the end of the search, the algorithm favors exploitation by decreasing the value of σ_k, which generates offspring solutions with similar characteristics to the parent generation.

Mutation

In each generation g, the standard deviation σ_{k_i} is first mutated using normal distribution to generate a new value σ'_{k_i}. Using the new value for the standard deviation, the parent, α_{k_i} is mutated to new individual α'_{k_i}. For the binary part of the chromosome, the mutation is realized by random bit-flips of the parent vector value; in this case, the standard deviation is used to determine whether the bit-flips will occur for the current parent gene. The mutant genes for the pipe location are selected from an array of topologically connected close conduits to the current parent. The distance of the offspring from the parent is determined by the mutated standard deviation. This will ensure that only conduits that are topologically adjacent to the parent genes are selected. The direction of the offspring search is determined by a specialized operator that maintains an external archive of distances to nearest SSO location for the parent genes. The search will move upstream at generation, $g + 1$ if the nearest SSO to the parent gene at g is upstream or the search will move downstream if the nearest SSO at g is downstream. The location of SSOs at g_0 is the location of SSOs under existing condition. The mutant for diameter increase genes is determined by the mutated standard deviation that is specified as an algorithmic parameter. For the decision regarding diameter increase, gene value less than 0.5 indicate that the segment will be increased by one commercial diameter. For values greater than 0.5 but less than 0.75, the segment will be increased by two commercial diameters and for values equal or greater than 0.75; the segment will be increased by 3 commercial diameters.

Selection

In ES-based search, the parental population at $(g + 1)$ is obtained by deterministic process that select best individuals from combined parents μ and offspring λ from g in what is known as $(\mu + \lambda)$ selection (Beyer & Schwefel, 2002). In this study, the NSGA-II selection is applied which is based on nondominance and crowding distance (Deb, Pratap, Agarwal, & Meyarivan, 2002).

METHODOLOGY

The proposed framework consists of two main parts: a modeling component and the optimization component. The modeling component involves the tasks related to pre-processing of GIS and hydrologic data to build and calibrate a hydraulic model of sanitary sewer collection and transmission systems. The optimization component relates to the problem definition (decision variables, objective functions and constraints), model connection and optimization algorithm. An overview of the framework with the modeling and optimization component interconnections is illustrated in Figure 2.

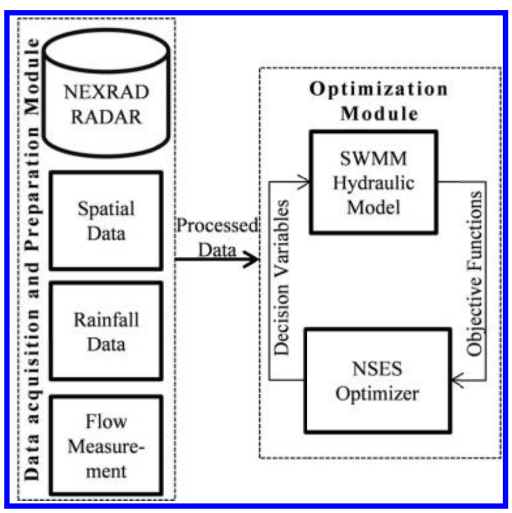

Figure 2. Schematic representation of the Modeling and Optimization components.

Modeling Component

The hydraulic model of the E-07-15 sewershed was built using a pre-processing GIS script tool that generates the input files to be imported into the modeling package EPA–SWMM.

GIS Pre-Processing:

A GIS pre-processing algorithm was implemented using the Python editor ArcPy to automate the generation of sanitary sewer models. The input GIS layers are: parcels, traffic analysis zone (TAZ), apartments, manholes, conduits, and rainfall gauges. The resulting algorithm generates final manholes, conduits, and subcatchments with populated information used in the model such as drainage area and population per subcatchment. The result algorithm generates a final manholes, conduits, and subcatchments with populated information used in the model such as: drainage area, population per subcatchment, land use (residential or commercial), conduits Manning's roughness, nearest rain gauge IDs and RADAR grid cell.

Model Calibration:

After the model was generated and imported into SWMM, a two-step calibration was performed. First, the sewershed was calibrated for dry weather flows (DWF), followed by one for wet-weather flows. DWF are continuous inflows that typically reflect the contribution from sanitary sewage in sewer systems or base flows in pipes and stream channels and is computed using the following equation:

$$Q_t^{DWF} = (P^{Res} \times \overline{WU}^{Res} + P^{Com} \times \overline{WU}^{Com}) \times K_t$$

where Q_t^{DWF} is hourly flow into a node (MGD), P^{Res} is the contributing residential population, P^{Com} is the contributing commercial population, $\overline{WU}^{Res}$ and $\overline{WU}^{Com}$ are the average water use for residential and commercial use, respectively (70 and 60 gallons per capita per day), and K_t is the hourly multiplier. SWMM allows the definition of DWF patterns for weekdays and weekends. 48 hourly multipliers were estimated using the nonlinear Generalized Reduced Gradient (GRG) optimization algorithm in Microsoft Excel to minimize the root mean square error (RMSE) between observed DWF and simulated DWF hydrograph for a typical weekday and weekend. Figure 3 shows the observed and simulated DWF hydrographs for a weekday and weekend measured in the South (ES19) metershed.

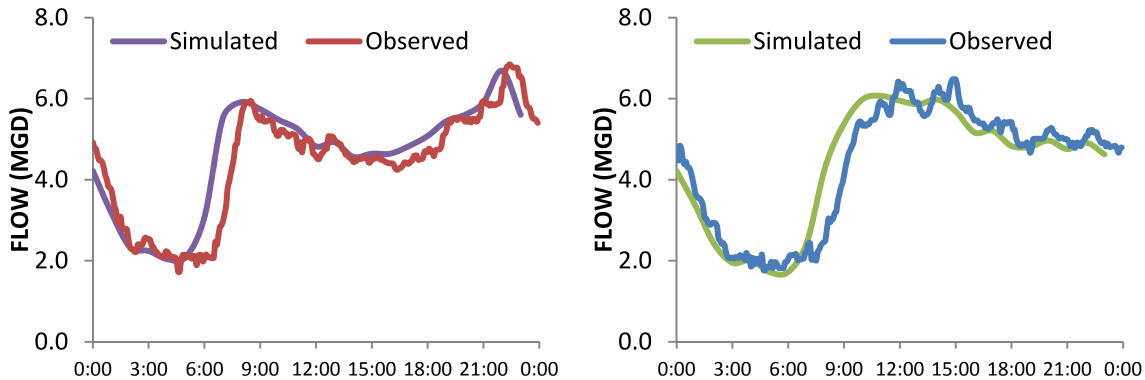

Figure 3 – Observed and simulated hydrographs during dry days for weekdays (right column) and weekends (left column) for the South (ES19) metershed.

A manual WWF calibration was performed using observed rainfall, NEXRAD radar, and flow data for three metersheds, which presented reliable flow data during the 2.12 inch storm event occurred on May 12th (Figure 4). In order to improve the rainfall representation, raw data of reflectivity recorded by the NEXRAD KEWX – AUSTIN/S ANT, TX, located in New Braunfels, TX, was processed and transformed to rainfall intensity in a five-minute interval and a spatial resolution of 0.7 kilometer grid cell size. SWMM calculates RDII using the RTK method (Walski, Barnard, & Haestad Methods, 2004), that fits three triangular hydrographs, each representing a rapid inflow, an intermediate infiltration and inflow, and a long-term infiltration period. Each hydrograph is defined by three parameters. R is the fraction of rainfall volume that enters the sewer system. T is the time from the onset of rainfall to the peak of the UH in hours, and K is the ratio of time to recession of the UH to the time to peak. Figure 4 shows the observed and simulated hydrographs and the rainfall intensity from May 12th to 14th.

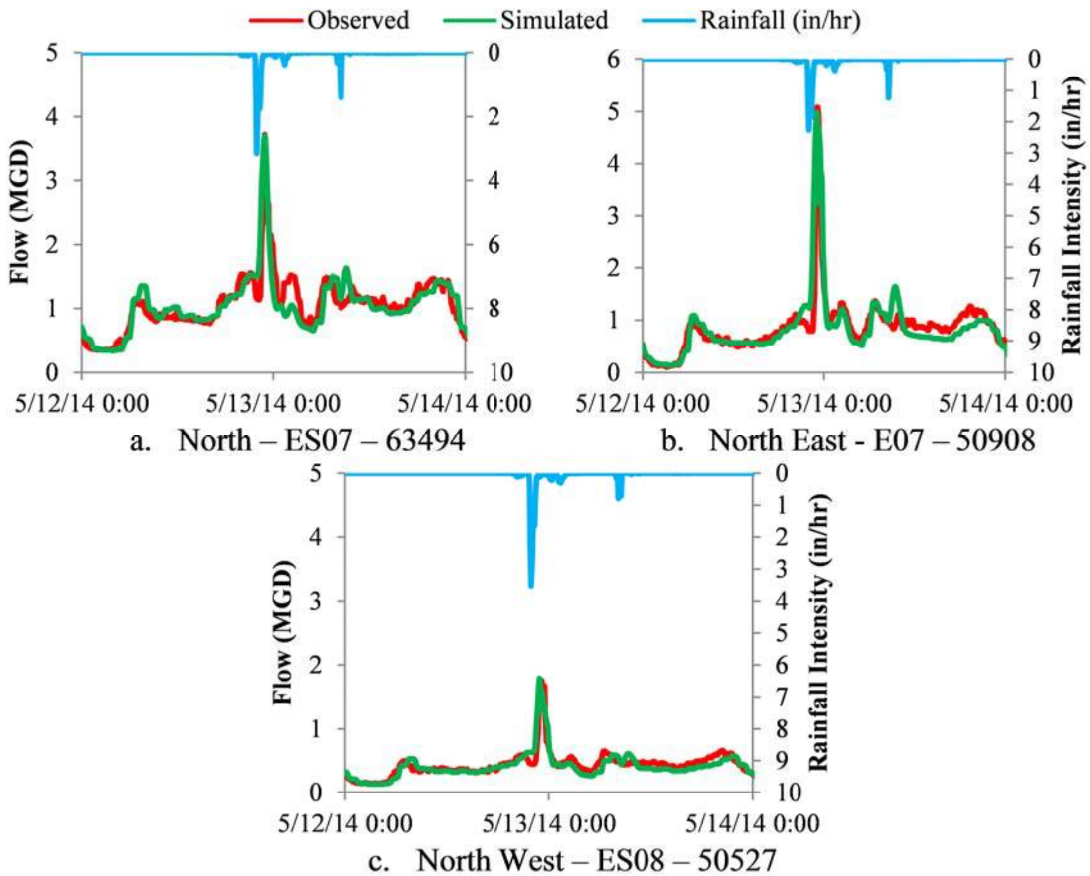

Figure 4 - Observed (red line) and simulated (green line) hydrographs from May 12th to May 14th 2014 (Event 1).

DISCUSSION AND ONGOING INVESTIGATION

The proposed optimization framework will be demonstrated for the realistic case of the E-07-15 sewershed and in the future is expected to be easily applied to other sewersheds in San Antonio. The use of the enhance NSES is expected improve the convergence time for SSO reduction optimization in comparison to results obtained from state of the art NSGA-II. The multi-objective optimization approach will identify a set of near-optimal solutions for rehabilitating sanitary sewer networks while reducing the occurrence of SSOs, which gives the managers more flexibility in the decision-making process. This approach helps define the tradeoff that exists between the occurrence of SSOs and the costs to reduce them by enhancing the conveyance capacity of sanitary sewer networks.

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